ABSTRACT

Title of Dissertation: THE STRATEGIC NETWORKS AND PERFORMANCE OF ENTREPRENEURIAL FIRMS: IMPACT OF PRE-FOUNDING TIES.

Shweta Gaonkar, Doctor of Philosophy, 2014

Dissertation directed by: Dr. Rajshree Agarwal
Ruldolph P. Lamone Chair and Professor in Entrepreneurship
Management & Organization

This dissertation examines the effect of founders' background in shaping alliance ties and firm performance of new ventures. In the first chapter, I examine how founders' prior affiliations contribute to the formation of network ties for new ventures founded by employee entrepreneurs. Prior research on employee entrepreneurship attributes the success of new ventures founded by employees (called *spinouts*) to knowledge inheritance from founders' previous employers (parents). However, studies on new venture alliances suggest that the success of new firms stems from establishing strategic alliances with other firms. I bridge the gap between these two literatures by examining how the knowledge accumulated by the spinout's founder influences the new venture's alliance partner choice, using a panel data of pharmaceutical and medical device firms

from 1986 to 2012. The findings suggest that a spinout that is similar to its parent in terms of technology and product markets is likely to form marketing, manufacturing, or funding ties with firms that have no parent ties. Conversely, a spinout that is not similar to its parent more likely to form commercialization ties with firms that have indirect ties to the parent, as a way to deal with the risk of collaborating with its parent and its partners. Finally, a spinout that has different technology but operates in a similar market, as its parent is likely to forge commercialization ties with the parent's partners.

In the second chapter, I examine how heterogeneity in the founders' backgrounds affects the start-up's performance. I examine two types of founder backgrounds: employee and academic entrepreneurs. Employee entrepreneurs have relevant industry experience due to their founders' prior affiliation, whereas academically founded firms are endowed with research-related resources through their founders' experience. I use the panel data of academic and employee start-ups in the pharmaceutical and medical device industry, 1986-2013. I find that academic start-ups have higher research output and smaller alliance networks than do employee start-ups. Further, the founders' background has no impact on the start-up's performance outcome; instead, it shapes the patents and alliance ties formed by them.

THE STRATEGIC NETWORKS AND PERFORMANCE OF ENTREPRENEURIAL FIRMS: IMPACT OF PRE- FOUNDING TIES

by

Shweta Gaonkar

Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, College Park, in partial fulfillment of the requirements for the degree of Doctor of Philosophy
2014

Advisory Committee:

Professor Rajshree Agarwal, Chair
Waverly Ding
David A. Kirsch
Martin Ganco
David B. Sicilia

Preface

This dissertation is submitted for the degree of Doctor of Philosophy at the University of Maryland. The research described herein was conducted under the supervision of Professor Rajshree Agarwal in the Department of Management and Organization at the Robert H. Smith School of Business. This work is, to the best of my knowledge, original, except where references are made to previous work.

This research was funded in part by the Ewing Marion Kauffman Foundation. The contents of this publication are solely the responsibility of Shweta Gaonkar.

Dedication

I dedicate this dissertation to my brother, Shravan Gaonkar, for without his early inspiration and support, none of this would have happened.

Acknowledgements

I would like to express my deepest appreciation to my committee chair, Professor Rajshree Agarwal, for her constant support and encouragement. I would like to thank her for supporting my research and for allowing me to grow as a researcher. Her advice on both research and career has been priceless.

I would like to thank my committee members Martin Ganco, Waverly Ding, David Kirsch, and David Sicilia for spending time evaluating my dissertation, and for providing useful comments and suggestions. A special thanks to Waverly Ding, who provided constant support and great suggestions to deal with the constant challenges faced during my PhD research. I would also like to thank Martin Ganco and Seth Carnahan for providing support and useful comments at all stages of my research. Thank you, Mahka Moeen, for providing me access to the Delphion database and for your support throughout my PhD.

I would like to thank my colleagues and friends at the department: Robert Vesco, Bryan Stroube, Justin Frake, Brad Greenwood, Daniel Olson, Justina Blanco, and Ying Geng for their many useful discussions, comments, and suggestions. I would also like to thank Abigail Gaonkar for inspiring me, and Xiang Bi for her support.

Finally, I would like to thank my husband, Angelo Mele, for his constant encouragement and advice throughout my PhD. My research would not have been possible without his support.

Table of Contents

List of Tables

List of Figures

Chapter 1: Casting Shadows: Effect of Parent-Spinout Knowledge Distance on New Venture Alliances

Introduction

One of the central tenets of the literature on spinouts posits that the success of new firms founded by employee entrepreneurs is a result of knowledge inheritance from successful parents (Agarwal, Echambadi, Franco, & Sarkar, 2004; Chatterji, 2009). Entrepreneurs in high-technology industries face severe competition, for both their technology and in commercialization of their products (Gans & Stern, 2003). The literature on new venture alliances suggests that these new firms cope with competition by forming alliance ties with other firms to gain access to complementary resources that are crucial for their success and performance (Podolny, Stuart, & Hannan, 1996). I bridge the gap between these two disconnected literatures by examining how knowledge inheritance from parent firms influences the ability of spinouts to establish network ties with other firms.

New firms differ in their access to resources and their ability to establish alliances ties with other firms. The founding conditions of the start-up determine its ability to learn and adapt in a competitive environment (Cohen & Levinthal, 1990). Firms founded by employee entrepreneurs inherit knowledge their founders learned from their previous employers or parent firms. Hence, founders with prior experience in a successful firm are more likely to create successful new ventures (Agarwal et al., 2004). However, the competition to survive and succeed in high-technology industries is fierce, with firms facing threats to both its technology and market entry. These new firms, even with their knowledge endowment through their founder's experience, continue to need complementary resources and use alliance ties to fulfill this need. I define a firm founded by an employee entrepreneur as a *spinout*, whereas the *parent firm* is the firm that employed these founders before creation of the spinout.

Employees gain social capital during their employment at their parent firms (Roberts & Sterling, 2012), and these networks influence their ability to form network ties in the future (Hallen, 2008). The imprint of prior organizational experience on the founders shapes their partner choices, especially for a new firm. Moreover, these alliance ties are crucial for firm performance because they provide valuable resources, information, and status (Davis & Eisenhardt, 2011). However, the literature does not extensively address the formation process of these ties among spinouts. This study extends prior studies on partner choice by examining the influence of the founder's prior affiliation on the external relationships established by these new ventures.

I address two key questions in this study. Do spinouts choose partners from their parent network? Moreover, what role does the inheritance of knowledge play in their partner choices? I capture a spinout's knowledge inheritance from its parent firm as a distance measure based on the technology and product markets of the parent and spinout. The technological and market distance measures allow me to classify these spinouts into four categories. Each spinout weighs its need for complementary resources with the risk of collaboration before establishing an inter-organizational alliance tie. A spinout enters into a tie with a partner when its resource need outweighs the collaboration risk.

I use data on firms in the pharmaceutical and medical device industry, collected using annual additions of Medical Marketplace guides. This data consists of firm, business unit, and top-management team data for firms in the pharmaceutical and medical device industry from 1986 to 2003. I supplement this data using COMPUSTAT for financial information, ventureXpert for funding information, LexisNexis for latest events, Corporate Affiliations for product information, Delphion for patent data, and ThompsonOne for individual-level data. The resulting unbalanced panel data contains network ties and firm- and individual-level data for the entire healthcare industry from 1986 to 2012. The data allows me to track the formation of ties for both spinout and parent firms in the pharmaceutical and medical device industry over time. The results show that spinouts with similar technology and markets as their parents will find partners with no parent ties to gain access to manufacturing, marketing, or funding resources. Conversely, spinouts with different technology operating in different product markets from their parents will form commercialization ties with firms that have indirect ties to their parents. This suggests spinouts deal with the collaboration risk by avoiding firms that have direct ties to their parent firm. Furthermore, spinouts that enter similar markets with different technology than their parents are likely to benefit from their parents' networks. These new ventures form commercialization ties with firms that have direct ties to the parents, suggesting spinouts can leverage their new technology relative to their parent to reduce the collaboration risk.

Theory

A founder's pre-founding experience has a profound effect on the creation of successful spinouts (Agarwal et al., 2004; Gompers, Lerner, & Scharfstein, 2005; Klepper, 2007). Spinouts inherit technical, marketing (Agarwal et al., 2004), and regulatory know-how from their parent firms (Chatterji, 2009), and the parents' characteristics dictate the spinouts' product spaces (Phillips, 2002). Occupying similar product space as its parent may limit a spinout's partner choices, implying that knowledge inheritance has an important role in the spinout's formation of alliance networks. Therefore, I classify spinouts based on their technological and product market distance with respect to their parent firm.

Employees learn valuable skills and build social networks through their experience in the parent firm (Gompers et al., 2005; Roberts & Sterling, 2012; Semadeni & Cannella, 2011). New ventures cooperate to aid commercialization of a product (Gans & Stern, 2003) and to gain access to complementary assets. In contrast, incumbents cooperate as an alternative to internal development (Rothaermel, 2001) or to control competition within the market. A start-up's network is determined by its founders' previous network connections (Hallen, 2008). Spinouts are an interesting setup to study new venture alliances because they allow examination of how prior affiliation, captured by the spinout's knowledge inheritance from its parent, affects the formation of alliance ties.

Founders can leverage their prior knowledge and social capital (accumulated during their employment at their parent firm) to access relevant information about complementary resources in other incumbents. They also can learn potential partner behavior while forming their alliance ties. To understand with whom these spinouts partner, and if they utilize their parents' networks, I categorize the partner firms into three categories: (1) the parent, or firms that have direct ties to the parent, called *parent direct ties*; (2) firms that have indirect ties to the parent, called *parent indirect ties*; and (3) firms with no ties to the parent, called *no parent ties*.

Knowledge Inheritance

In a high-technology industry, knowledge and access to resources are the key success determinants for a new venture. A new venture's superior performance is contingent on its ability to formulate a cooperative strategy (Ahuja, 1996) and on knowledge inheritance from its parent firm (Agarwal et al., 2004). Network ties serve as a source for innovation, resources, and capabilities (Kogut, 1988). These alliance ties have a long-lasting influence on the spinout's performance. However, differences among the cooperative strategies employed by the spinouts relate to heterogeneity in the level of knowledge inherited from their parents. Therefore, I classify spinouts based on the inherited knowledge in both market space and technological space.

I use market distance and technological distance to measure a spinout's knowledge inherited from its parent firm. Both measures capture the Euclidean distance between two firms based on the technology and product markets in which both firms exist. *Market distance* is defined as the extent to which the products of a spinout differ from those of its parent. Product market strategy is at the heart of the firm's strategy to achieve competitive advantage (Makadok & Ross, 2013), and the influence of knowledge inheritance extends to the product markets these spinouts enter (Phillips, 2002).

Therefore, a spinout's market choice relative to its parent's product market affects how it shapes its alliance network.

Technological distance captures the technical knowledge the spinout inherits from its parent. I note that not all technical knowledge within firm maps to its products. Additionally, a firm might choose to abandon a technological field and just license their technology to other firms. Thus, I capture technology with a measure different from market distance. If the technological distance is high, then a spinout is in a different technological space from its parent's space. On the other hand, low technological distance implies that the spinout imitates parent firm knowledge.

Spinout Categories

Technological and market distance from the parent may shape the spinout's partner choices. I start by classifying spinouts into four categories (Figure 1) based on their technological distance and market distance. Spinouts in the first category inherited technical knowledge from their parents and chose to enter a product market similar to their parents. These firms have low technological and market distance from their parent firms. Because they "imitate" the technical and market knowledge of their parents, they end up competing with limited resources against the parent firm. These spinouts may also face competition also from firms in proximity to their parents' markets. The threat of appropriation from their parent firms is high; therefore, these spinouts may seek partners that are distant from the parent firm, but interested in gaining access to knowledge within the spinout.

_ _

Insert Figure 1 (Spinout Categories) here

In the second category, spinouts choose to apply the knowledge inherited from their parents in a product market different from their parents' market. These spinouts "adapt" to new markets relative to their parents and do not compete directly with their parents. Further, this provides an opportunity for the parent firm and its collaborators to enter into new product markets by forming alliance ties with the spinouts.

The third category of spinouts enters a product market similar to their parents' but is distant on the technical knowledge dimension from the parents. Given the application of new technology in the same product market space, this type of spinout competes with the parent by using technologies that may potentially disrupt the parent's technological capabilities. While firms in the parent network may be interested in leveraging the different technology, they also pose a potential threat of appropriation. Accordingly, while there is a likelihood of alliance formation with firms in the parent network given complementarities between spinout technical knowledge and their relevant complementary assets, spinouts may proceed cautiously.

The final category of spinouts "explores" new product markets relative to their parents' product markets, using new technology with respect to their parent firms' technology. These spinouts use neither technical nor market knowledge from their parents and, as a result, do not directly compete with their parents.

Proclivity to Form Ties: Need versus Risk

A key driver of inter-organizational alliance ties is the need for complementary resources (Gulati, 1999). An alliance tie is established when two organizations have mutually beneficial resources or capabilities. The need for resources could go beyond financial resources and include resources required for accessing a market (Aiken & Hage, 1968). Regulatory resources are one such resource crucial to gaining market access in the medical device and pharmaceutical industry. Successful spinouts in this industry inherit regulatory, in addition to the technical and market, knowledge from their parent firms (Chatterji, 2009).

New firms have limited resources (Fichman & Levinthal, 1991) but can access these unique resources through their partner firms (Katila, Rosenberger, & Eisenhardt, 2008). On the other hand, incumbents seek partners to enter into new or emerging technological subfields to deal with their incumbency (Mitchell & Singh, 1992). Compared to a new firm, the incumbent has different resource needs but the same motivation to form alliance ties—namely, to access resources within partner firms. Scholars have examined the role of firm attributes such as size, age, and financial attributes in predicting the proclivity of a firm to form a tie (Burgers, Hill & Kim, 1993; Kogut, Shan, & Walker, 1992). However, resource needs might be the key factor determining a firm's decision to enter into an alliance. Firms manage their need for resources by seeking strategic ties to partners who help fulfill the needs (Schmidt & Kochan, 1977). This need for resources or capabilities might, in fact, moderate the pattern of inter-organizational alliance ties that the firm establishes (Nohria & Garcia-Pont, 1991).

On the other hand, collaborating to gain access to complementary resources is not without risk. Collaboration risk for a new venture stems from potential partner behavior in an alliance. The partnering firm could choose not to contribute to the alliance and withhold its efforts. Additionally, the partner could misappropriate resources (Gulati & Gargiulo, 1999) from the new firm, rendering the new firm vulnerable without its valuable resources. Incumbents rely on their alliance ties to gather information regarding their partners' behavior. They are more likely to partner with firms with whom they had prior alliance experience (Gulati, Lavie, & Singh, 2009). Absent prior alliance ties, new ventures rely on their founders' prior affiliations to gain information about their partners. In addition to these concerns, spinouts continue to face competitive pressures from their parent firms. As a result, prior affiliation plays an important role in shaping the strategic alliance ties established by new ventures.

Role of Prior Founder Affiliation

Spinouts inherit technical and market knowledge from their parents, and this knowledge drives their resource needs. On the other hand, the technological and market distance between a spinout and its parent firm also dictate the collaboration risk. Spinouts in close technological or market proximity to their parents compete for resources in both spaces, increasing the threat of resource appropriation for the spinout, whereas greater technological and product market distance implies a lower level of competition. As a result, these distances capture the spinout's need for resources as well as its risk in collaborating with a potential partner.

A network tie between two firms is established when the tie is mutually beneficial. However, the true value of a network tie is not realized ex-ante. Hence, firms seek out partners based on the potential partner firms' characteristics. A spinout will weigh its need for resources against the risk of collaboration with its partner. The literature on network formation among firms has examined the network formation process as an attempt by firms to gain access to critical resources (Gulati, 1999) while avoiding partners that could behave opportunistically. Further, inter-organizational alliance networks serve as conduits of information about potential opportunistic behavior of firms (Gulati & Gargiulo, 1999). Absent network ties, new firms cannot access information regarding opportunistic behavior of their potential partners. New firms, then, must rely on alternative sources of information. Spinouts rely on their founders' prior experience to access the information required to determine the attractiveness of potential partners. The founders' social capital allows spinouts to access information about complementary resources within the parent, or firms with ties to the parent, and about the behavior of their potential partners. Spinouts use this information to seek out partners that meet their resource needs with minimal risk of opportunistic behavior.

Forming network ties with other firm benefits the spinout. Such collaborative ties allow the spinout to access complementary resources in partner firm and help gain legitimacy in the industry (Podolny, 1993). However, forming ties is not without its pitfalls, especially for new ventures. Firms entering new ties face concerns about the hazard of partners behaving opportunistically (Hamel, Doz, & Prahalad, 1989; Williamson, 1991). A partner may simply behave opportunistically by limiting its contribution or by taking advantage of the relationship to misappropriate valuable resources. Misappropriating spinout resources may be tempting for an incumbent and could hinder the spinout's success or survival. Firms minimize the risk of opportunistic behavior by accessing information about the partner's reliability through their current networks (Gulati, 1995a; 1995b). This information is crucial, especially when survival and success depend on partner behavior (Bleeke & Ernst, 1993). Spinouts that do not have prior ties tend to rely more on the founders' social capital to access similar information. Therefore, the new firm's origin is crucial in shaping their network.

For an incumbent firm, forming network ties with a new venture is an alternative to developing technology or a product internally (Rothaermel, 2001). Spinouts, whose employees inherit knowledge and use the knowledge to create similar or different products, are specifically attractive to incumbents. At the same time, the long road to product commercialization is laden with difficulties (Gans & Stern, 2003) for employee entrepreneurs in high-technology industries because of their limited resources. Therefore, an incumbent seeks partners in order to enter new technical subfields and offers resources to commercialize the product. For example, Eli Lilly entered into an alliance with Genentech, which held the proprietary technology for human insulin based on recombinant DNA (Humulin). Genentech decided to license the technology to Eli Lilly instead of producing it on its own (Lee & Burrill, 1994). This was an opportunity for Eli Lilly to enter the market with new technology licensed from a new venture.

Spinouts seek partners that fulfill their own resource needs while minimizing the risk of losing resources to the partners. An alliance tie will allow the spinout to access resources within its partner firm. Prior research has shown that forming an alliance tie reduces uncertainty, and both firms gain access to crucial resources from the other partner (Pfeffer & Slancik, 1978). New ventures form ties despite their concerns about the hazards of opportunistic behavior by partners—when the partners provide the unique resources they need (Katila et al., 2008). However, a spinout can overcome the risk of misappropriation by their partner by using the founder's social capital to access relevant information about the partner's behavior (Gulati, 1995b). Because the spinout relies on its founder's social capital—accumulated during tenure at the parent firm—the parent continues to cast a shadow on relationships forged by the spinout. That is, knowledge inheritance shapes the resource needs and the risk of collaborating with firms that have direct or indirect ties to the parent.

Formation of Spinout Alliance Ties

The founder's prior experience creates certain path dependency in the search for partners. Absent prior alliances, spinouts are limited to searching locally for partners because of their organizational and relational context (Rosenkopf & Almeida, 2003). Usually, this means searching for firms that have direct or indirect ties to the parent. Partners with direct or indirect ties to the parent firm provide opportunities for the spinout to access complementary resources, similar to those of its parent, but the collaboration risk may differ for these two types of partners. Furthermore, the founder's prior affiliation to the parent firm acts as a source of information regarding these firms. Firms with direct ties to the parent firm are a good source to gain access to the complementary resources the young firm needs.

However, spinouts that continue to face collaboration risk due to tension between the parent and the spinout could choose to access these resources while distant from their parent's immediate network. A spinout's resource needs and capabilities drive its alliance-partner selection. In addition, the firm's social context limits its search for resources (Eisenhardt & Schoonhoven, 1996; Gulati, 1995a). In the case of the spinouts, their founders' prior affiliations strongly influence their social context. By the virtue of their founders' experience in the parent firm, these spinouts have information about the firms that have direct and indirect ties to the parent. Any firm beyond the second level of ties to the parent is too distant, reducing the probability the founder had a relationship with them during their tenure in the parent firm. The level of collaboration risk could vary across firms that have direct or indirect ties to the parents.

Resource needs and collaboration risk are influenced by the technological and market distance between the parent and the spinout. The technological and market distance shapes the resource needs as well as the collaboration risk, but also translate to opportunities to form ties with firms within or outside of the parent network. I define these potential partners as firms with parent direct ties, parent indirect ties, and no parent ties. Each network level implies different opportunities to fulfill resource needs, along with different levels of collaboration risk.

Firms with direct ties to the parent firm have resources relevant to spinouts that use their parent knowledge due to their founders' imprint on the new venture (Agarwal et al., 2004; Franco & Filson, 2006). These firms would be lucrative options for alliance partners. However, a spinout inherits competition, along with the knowledge, from their parent. Similarity in knowledge implies fierce competition between the parent and spinout, making the alliance with the parent firm or its partners prone to collaboration risk.

The second category of partners is firms with indirect ties to the parent. These firms can provide resources similar as the parents' resources. Further, not having any direct tie to the parent implies a lower collaboration risk for the spinout. However, it is more challenging for spinouts to search for these partners, as they cannot search in proximity to the parent firms. Nevertheless, spinouts benefit from ties with firms that have indirect parent ties; they can fulfill their resource needs and avoid the risk associated with collaborating with parent partners. Furthermore, spinouts can leverage their founders' experience to search for partners within firms that have direct or indirect ties to the parent. They can access information about a potential partner firm's behavior through their founders' pre-entry experience.

The final set of partners is firms that have neither direct nor indirect ties to the parent firm. If the collaboration risk is too high and the competition too fierce between the parent and spinout, then the spinout is likely to search for firms with no parent ties. Additionally, if the spinout is not similar to the parent, they are likely to seek partners that have resources relevant to the market of entry (Helfat & Liberman, 2002). In sum, each type of partner (Figure 2) represents a different level of collaboration risk and ability to fulfill resource needs.

Insert Figure 2 (Partner Types) here

If the spinout is similar to its parent, then competition between the parent and the spinouts is fierce. For these spinouts, forming an alliance tie with a parent or other firm with direct or indirect ties to the parent is a risky undertaking. Spinouts that have low technological and market distance are the classic "imitators" described in spinout literature (Agarwal et al., 2004; Franco & Filson, 2006). These spinouts are similar to their parents with respect to both their products and their technology. Hence, competition in their parent product market makes formation of alliance ties to firms with direct or indirect parent ties prone to collaboration risk. The collaboration risk level differs for firms that have parent direct, parent indirect, or no parent ties. Similarly, the types of resources that could fulfill the spinout's needs vary across these three partner types.

Spinouts that are similar to their parents compete in the same market and with similar technology as the parents. Therefore, the parents and parent partners can provide access to resources that are relevant to the market of entry for these new ventures. Clearly, forming ties with firms that have direct ties to the parent will fulfill the spinout's resource needs. Moreover, spinouts will pursue alliance ties with firms that have direct parent ties to fulfill their resource needs if they do not anticipate any collaboration risk.

Hypothesis 1a. Spinouts with low technological distance and low market distance with respect to their parents are more likely to form ties with firms with direct ties to their parent firms.

Compared to firms with direct ties to the parent firm, firms with indirect parent ties have relevant resources for the spinout to fulfill its needs and lower collaboration risk. For a spinout that has similar technology and product market as its parent, firms with direct parent ties continue to offer the resources the spinout seeks but with higher collaboration risk than firms with indirect parent ties. Therefore, when a spinout is likely to benefit from resources within firms with indirect parent ties—and these resources are crucial, complementary assets required for the spinout's success—the spinout might risk forging these ties.

Hypothesis 1b. Spinouts with low technological distance and low market *distance with respect to the parents are more likely to form ties with firms that have indirect ties to their parent firms.*

Conversely, spinouts with low technological and market distances compete directly with their parent firms because they imitate both technical and market knowledge. This competition increases their concern about potential opportunistic behavior by firms with direct or indirect ties to the parent. This would imply that the risk of collaboration with firms with either direct or indirect ties to the parent outweighs the benefits of access to complementary resources within those firms. Hence, these spinouts seek partners that have no ties to their parent firm.

Hypothesis 1c. Spinouts with low technological distance and low market distance with respect to the parents are more likely to form ties with firms that have no ties to their parent firms.

Spinouts that have high technological and market distances from their parent firm create new knowledge, unrelated to their parent's products or technology, while operating in a different market than their parents do. However, founders can leverage their accumulated social capital, gained through their prior employment, to establish external relationships (Hallen, 2008). These prior ties create path dependencies regarding partner choice. Firms that have direct or indirect ties to the parent could be a good source of complementary resources relevant to the spinouts' market entry. Spinouts rely on their founders' prior affiliations and seek partners within their parent networks to fulfill their need for complementary resources. The founders 'social capital allows these firms to access information regarding their potential partners' behavior, which would reduce the risk, associated with collaboration. In sum, the complementary resources within the firms that have direct ties to the parent will fulfill the spinouts' resource needs, and the founders' prior affiliations offset the collaboration risk. As a result, these spinouts tend to form ties with parent partners and not with firms that have indirect or no parent ties. Hence,

Hypothesis 2a. Spinouts with high technological distance and high market distance with respect to the parents are more likely to form ties with firms with direct ties to their parent firms.

Spinouts that are in different product markets and have different technology from their parents do not face stiff competition from their parents. This difference in market and technology lowers, but does not eliminate, collaboration risk. The risk is lower with firms that have indirect ties to the parent. Moreover, spinouts can leverage their founders' experience to search for firms that have indirect ties to the parents and can fulfill their resource needs. These spinouts are more likely to form ties with firms that have indirect ties to the parent and avoid firms that have direct or no parent tie. Hence,

Hypothesis 2b. Spinouts with high technological distance and high market distance with respect to the parents are more likely to form ties with firms that have indirect ties to their parent firms.

On the other hand, these spinouts do not have any related technical or product knowledge with respect to their parents. Hence, these firms would seek a partner in their market of entry (Helfat & Liberman, 2002) or one with no ties to the parents. These spinouts are not entering the parent market; therefore, firms with direct or indirect parent ties would not necessarily hold relevant complementary resources for the spinouts. Additionally, the spinouts could face collaboration risk if they form ties with firms that have either direct or indirect ties to the parent network. As a result,

Hypothesis 2c. Spinouts with high technological distance and high market distance with respect to the parents are more likely to form ties with firms that have no ties to their parent firms.

The third category of spinouts is new ventures that have high technological distance from their parents, but operate in similar product markets. These spinouts seek complementary assets relevant to their market of entry (Helfat & Liberman, 2002)—the parent market, in this case. Firms with direct or indirect ties to the parent operate in a product market similar to the parents and have resources relevant for the spinout product market.

These spinouts introduce products in the parents' product market space but with different technology. The spinout's technology poses the threat of making the parents' technology obsolete. As a result, these spinouts also pose a threat to the technology within the parent and to the parents' direct or indirect partners.

Spinouts with high technological distance but low market distance can leverage their founders' prior affiliation to seek partners among firms that have direct parent ties. These ties offer the complementary resources that the spinouts need, especially when operating in a similar market as their parents. However, each partner category holds different risk levels. In this category, the spinouts hold bargaining power as they enter similar markets with different technology from their parents. Hence, they can reduce collaboration risk and reap alliance benefits by forming ties with firms that have direct ties to their parent as opposed to indirect or no parent tie.

Hypothesis 3a. Spinouts with high technological distance and low market distance with respect to the parents are more likely to form ties with firms with direct ties to their parent firms.

When spinouts operate in a similar market as their parent, they may search for alliance partners based on their founders' pre-entry experience. If a spinout perceives a high risk when forming ties with firms that have direct parent ties, then it can fulfill its need for complementary resources by forming ties with firms that have indirect parent ties as compared direct or no parent tie.

Hypothesis 3b. Spinouts with high technological distance and low market distance with respect to the parents are more likely to form ties with firms that have indirect ties to their parent firms.

Alternatively, these spinouts face fierce competition from firms with direct or indirect parent ties by the virtue of having different technology relative to their parents. This competition could increase the collaboration risk; partner firms could potentially misappropriate spinout resources. Additionally, because these spinouts operate in different markets than their parents, they could seek partners from the different markets. Hence, these spinouts seek partners outside of their parents' direct or indirect network to access complementary resources relevant to their market of entry while minimizing collaboration risk. Therefore,

Hypothesis 3c. Spinouts with high technological distance and low market distance with respect to the parents are more likely to form ties with firms that have no ties to their parent firms.

Unpacking Resource Requirements

Spinouts create alliance ties to gain access to resources. The obvious next question is what resources are being transferred across these ties. These young firms have to engage in long periods of research and development (R&D) before introducing a product into the market. They support themselves by seeking resources from other organizations. Spinouts that choose partners within or outside parent networks seek different resources. I define five types of resources: research, commercial, manufacturing, funding, and marketing resources.

Research resources relate to any R&D activity the spinout undertakes. Commercial resources allow the firm to commercialize their product or introduce it in the market. A firm uses manufacturing resources in its production process and marketing resources to market or distribute its product. Funding resources include the various forms of funding a firm receives, and range from venture funding to bank loans. A young firm could also fund itself by giving the overseas marketing or manufacturing rights of one of its products to other firms. These funds would in turn be used to finance the R&D associated with their core technology. Hence, I group marketing, manufacturing, and funding resources into one category.

Do these spinouts seek specific resources when they form ties with firms that have direct or indirect ties to the parent firm? When spinouts seek partners that directly or indirectly relate to their parents, they gain information about their potential partner behavior through their founder. These spinouts can scope out potential partners for their behavior and avoid collaboration risk by gathering information through their founders' prior experience. As new ventures, spinouts need resources to aid their commercialization process. Most spinouts like to control R&D of their core products and are therefore unlikely to seek research resources. Instead, they search for partners to fulfill their commercialization resource needs and avoid research ties with firms that have either direct or indirect parent ties to avoid collaboration risk. Hence,

> *Hypothesis 4: Spinouts that form ties with firms that have direct or indirect ties to their parent are most likely to seek commercialization resources.*

What resources are transferred across a tie when spinouts partner with firms that have no ties to the parent firm? Spinouts that seek partners with no ties to the parent cannot rely on their founders' prior affiliation to collect information about the potential partners. In this case, collaboration risk is very high due to lack of information about potential partner behavior. Therefore, forming ties to transfer research or commercialization resources is risky. These ties deal with core firm technology; the firm could expose itself to potential exploitation by its partner. As a result, these spinouts seek only marketing, manufacturing, and funding resources from partners with no parent ties. Thus,

Hypothesis 5: Spinouts that form ties with firms that have no ties to their parent firm are most likely to seek marketing, manufacturing, and funding resources.

Data and Methodology

I test these hypotheses in the context of the pharmaceutical and medical device industry. This industry provides an ideal empirical context to study inter-firm tie formation for three reasons. First, the industry is highly competitive; innovation is key to success. Second, the industry is highly regulated. The U.S. Food and Drug Administration (FDA) approval is one of the key steps to introducing the product into the market. As such, highly competitive industry resources related to regulation and manufacturing plays a crucial role in the firm's success. Hence, a new venture needs access to crucial complementary resources, such as marketing resources, or to resources to overcome market regulations. The need for constant innovation in the face of regulatory barriers to market entry fuels collaboration across firms. Thus, a firm can choose to diversify its strategic network ties with equity ties (Santos & Eisenhardt, 2009), nonequity ties, or joint ventures (Helfat & Lieberman, 2002). Finally, the R&D stage in the pharmaceutical and medical device industry is too long for young firms to survival without external support.

New ventures provide a unique opportunity to examine how networks emerge from the inception of the firm. One of the challenges of studying new venture alliances is the difficulty collecting data on young firms whose information is not publicly available and data on founder backgrounds. I am able to overcome these challenges by using data from Medical and HealthCare Marketplace Guides between 1986 and 2003. I digitize these books to create a unique database that contains firm-, division-, and individual-level data for firms in the healthcare industry. It contains data for about 10,000 firms in the pharmaceutical and medical device industry from both U.S. and outside-U.S. locations.

This database contains 2,549 new firms founded after 1973, and I identify the founding team for each firm. I define the *founding team* as the top management team of the firm during the first 5 years from the founding year. This definition works well, as the founder has a strong influence on the selection of the top management team. Even if this top management team changes, the composition of the initial team remains the same; and the founders' influence persists in the choice of future top management teams (Beckman & Burton, 2008). To classify these firms as spinouts, I track employment history of the top management of all 2,549 firms. If one member of the top management team worked at an incumbent firm prior to the founding year of the new firm, then I classify the firm as a spinout. I repeat this process using ThompsonOne data to track the employment history of the top management team within the first three years of founding. By tracking prior employers, I identify 296 spinouts in the pharmaceutical and medical device industry: 182 (62%) in pharmaceuticals, 78 (26%) in medical devices, and 36 (12%) in both. I update the data on spinouts from the Medical Marketplace database in the pharmaceutical and medical device industry to the year 2012 by collecting data from LexisNexis, the U.S. Securities and Exchange Commission (SEC) filings, COMPUSTAT, Delphion, Corporate Affiliations, ventureXpert and ThompsonOne. The resulting dataset is a panel data of pharmaceutical and medical device firms from 1986 to 2012.

I combine data from the Medical Marketplace database with net sales, gross profit, number of employees, and R&D expenses from COMPUSTAT. I extract the initial public offering (IPO) year from the Medical Marketplace data, COMPUSTAT, and ventureXpert; and the year of first funding from ventrueXpert. I track the four-digit product standard industrial classification (SIC) code from Corporate Affiliations and Medical Marketplace data. I supplement the entry and exit years of each product market for each firm with information from the Medical Marketplace data. I collect post-2003 network information from LexisNexis and Securities Data Company databases and use this data to plot the spinout ego network (Figure 3) for only network ties between the spinout and other firms. I collect patent data for the spinouts and their parents from the Delphion database. The result is an unbalanced panel data of spinouts in the pharmaceutical and medical device industry from 1986 to 2012.

An *alliance tie* in my empirical context is any formal relationship established between two firms in order to gain access to resources within the other firm. A formal tie between two firms could take any form of formal relationship, such as collaboration or agreements, joint venture, alliance, equity, and nonequity ties. With the aid of the

Medical Marketplace data, I am able to collect data on collaboration among firms and, specifically for this study, data on new ventures founded by employee entrepreneurs. However, this data ends in 2003; to make the data current, I combine it with data from the LexisNexis database and SEC filings. This rich data on firm collaborations provides information regarding the year of tie formation, resources transferred across the tie, and type of relationship. This unique data allows me to examine the network ties the spinouts formed, from inception to 2012.

Knowledge plays a vital role in the success and survival of firms in high-technology industries. However, knowledge can be divided into the two dimensions of technology and market. It is important to differentiate between these two forms of knowledge because not all technical knowledge within a firm transforms into a product in the market. Distinguishing between the two knowledge dimensions allows us to understand how spinouts inherit knowledge from the parent and which type of knowledge inheritance plays an important role in shaping the spinout's strategic networks.

Technological knowledge is captured using a distance measure based on patent class. I collect patent data for each firm from the Delphion database and use it to create the measure *TECHDIST*. This measure captures the distance between two firms in technological space using the distribution of patents across the various patent technology classes. It allows me to measure technological distance between any two firms, and especially between a parent and a spinout. I use the average share of patents per firm in each technology class and define a vector

$T_i = (T_{i1}, T_{i2}, T_{i3},\ldots T_{i426})$, where T_{ik} is the share of patents of firm *i* in technology class *k*. The technology market information for patents is classified into 426 markets (Bloom, Schankerman, & Reenen, 2013).[1] Then, I define the TECHDIST between two firms *i and j;* using an index:

$$TECHDIST_{i,j} = \frac{\left(T_i T_j'\right)}{(T_i T_i')^{1/2}\left(T_j T_j'\right)^{1/2}}$$

This index ranges between 0 and 1, depending on the degree of distance in technology class, and is symmetric to firm ordering, so that $TECHDIST_{ij} = TECHDIST_{ji}$.

Patents provide a relevant measure of technology in the pharmaceutical and medical device industry and provide firms with fairly strong protection for their proprietary knowledge. As products of a firms' innovation, patents represent a valid measure of technological novelty within the firm (Griliches, 1990). Patents have been shown to relate closely to technological strength (Narin, Elliott, & Ross, 1987) and correlate highly to innovation and invention counts.

There are limitations to using patents as a measure, for two main reasons. First, not all inventions or innovations are patentable. Patentability varies across industries, but is not the case in this study. Patents are crucial for a firm in the pharmaceutical and medical device industry to protect technical knowledge. A second issue could arise because firms' propensity to patent may vary (Cohen and Levin, 1989). However, new and incumbent firms in high-technology industries protect their intellectual property

---

1. Bloom et al.'s (2013) measure modified the Euclidean distance measure to better capture both technological knowledge and market distance based on patent main class and product sales in each of the markets is defined by the respective SIC codes. This index is also a modified version of Jaffe's (1986) cosine index to measure similarity of technology based on patent classes.

fiercely (Agarwal, Ganco, & Ziedonis, 2009). Hence, in context of this study, patents are a good way to capture technological distance.

To measure market knowledge, I construct a similar measure for product market distance using the presence of a firm in each market segment, defined based on the four-digit SIC code. Although the SIC code is a good measure of markets in which the firms operate, it is a very aggregated measure of products within the firms. An alternative would be to create a classification system based on the complete product list of each firm. Although I have the data to do this, one of my major concerns in using such a system is that some products would not be comparable. Therefore, maintaining a consistent classification system across the industries would not be feasible using product-level data as the market measure. Instead, using the SIC system worked well to generate a market distance measure. I define the presence of a firm in each industry code by a vector S_i = (S_{i1}, S_{i2}, S_{i3},… S_{in}), where S_{im} is the dummy of firm *i's* presence in the product market *m*. The market distance is operationalized as:

$$MRKTDIST_{i,j} = \frac{(S_i S_j')}{(S_i S_i')^{1/2}(S_j S_j')^{1/2}}$$

This measure ranges from 0 to 1, depending on the degree of distance in technology class, and is symmetric to firm ordering, so that $MRKTDIST_{ij} = MRKTDIST_{ji.}$

I collect four-digit SIC code information on these firms from the Medical Marketplace, Corporate Affiliations, and LexisNexis database. Using the identified market classes, I create a unique set of classes S_i to generate the market distance measure. The patented technology and products of the spinout is used to define the knowledge distance between parent and spinout. The spinout may inherit knowledge and then patent it. However, it may choose not to compete in a similar product market as its parent or choose to use a different technology in the parent market. Therefore, this becomes an important distinction when classifying the spinouts (Figure 1). Market distance is classified into two categories (high or low) through a cutoff value of the median of the distance measure (0.23). Similarly, the technological distance is divided into two categories (high or low) using a cutoff value of the median of that measure (0.45). Spinouts are classified based on the two categories *technological distance* and *market distance*.

– –

Insert Table 1 (Variable Definitions) here

– –

Thus, spinouts are classified into four categories based on the above definitions. There are 235 spinouts with complete patent and product data from the initial sample of 296. Of those 235 spinouts, the classification process yields:

- 151 (64%) with low technological and market distance
- 59 (25%) with high technological and low market distance
- 15 (6%) with high technological and market distance
- 10 (5%) with low technological and high market distance

The 235 spinouts have 825 partner firms. As extended, the partners of these 825 partners, spinouts, parents, and partner firms totaled 3,195 firms. I generate dyad level data for spinouts by creating a dyad where each spinout has an opportunity to form ties with any of the remaining 3,194 firms. The summary statistics of all the variables are shown in Table 2.

– –

Insert Table 2 (Descriptive Statistics) here

– –

Dependent Variables

The key dependent variable captures the different types of partner firms based on the presence or absence of ties to the parent. The three groups of partners are direct, indirect, or no parent ties. The first group includes the parent and firms that have direct ties to the parent firm. The second group consists of firms that are partners of the parents' partner firms or that have indirect ties to the parent. Finally, the firms that have neither direct nor indirect ties to the parent compose the third group, partners with no parent ties.

Based on these partner type definitions, I generate the first dependent variable "parentNetwork." This variable takes the values: 1, firms with direct ties to the parent; 2, firms with indirect ties to the parent; 3, firms with no ties to the parent; or 0 otherwise.

To further understand the formation of inter-organizational ties among spinouts, I examine the type of resources transferred across these ties. For this analysis, I create a second dependent variable that takes a value of 1 to 3 for research, commercial, and marketing or funding resources, respectively. This variable takes the value of 0 when there are no ties between the two firms.

Independent Variable

The key independent variable captures the different types of spinouts. To understand how knowledge inherited by a firm founded by an employee entrepreneur influences networking behavior, I categorize the spinouts based on their technical and market knowledge. This yields four dummies for each type of spinout.

In the first category, spinouts have low technological distance and low market distance from their parent firm. These spinouts imitate the knowledge of their parent. In the second category, spinouts have high technological distance and high market distance. These firms do not inherit any knowledge from their parents. The third category is spinouts that have high technological distance and low market distance. These firms enter the parent market with disruptive technology. The final category is spinouts that have low technological distance and high market distance. These spinouts enter the new market with knowledge inherited by the parent. This final category is the control group for my analysis.

Control Variables

I control for spinout characteristics such as age, number of patents, patent citation, number of employees, and location. Incumbents could find partners among the new ventures when they find the technology within the spinout attractive. Therefore, I control for spinout partner technological and product market distances. I also control for incumbents’ characteristics such as their patents and network centrality. *Network centrality* is an important measure to understand how a spinout with ties can position itself in a network to best gain from its network ties. The central player is assumed to have access to the best resources. Spinouts enter with a disadvantageous situation: by inheriting knowledge from the parent firm, they are competing with the parent. However, forming ties with other firms allows the spinout to compete with other firms in its product market. Although new ventures may lack the prior alliance ties that incumbents’ possess, they can leverage their prior affiliation with their parents and their knowledge to form ties. Forming alliance ties with incumbents helps ensure the spinouts gain access to critical complementary resources early and helps legitimize (Podolny, 1993) the spinout in the industry. This provides the new venture an opportunity to leverage these ties to form more ties with other prominent firms and improve its network position, especially centrality. Hence, I include controls for "betweenness" centrality of parent and partner firms because it captures the flow of information across firms. I also control for parent and partner characteristics, such as the number of patents, using a count or a dummy and number of ties.

Methods

There are two parts to this analysis: estimating tie formation with different types of partners and analyzing the resources transferred across these ties. For the first part, I use exponential random graph models (ERGM).[2] Additionally, I use multinomial logistic regression to see if these findings hold and to estimate the different types of resources accessed through the ties.

Estimation Using ERGM

To understand processes that influence network formation (Hypotheses 1-3), I

2. The ERGM is important when analyzing tie formation. The key difference between logistic regression and ERGM is that logistic regression analyzes only the ego network, whereas ERGM estimates tie formation based on the complete network of all firms. The ERGM estimation considers simultaneous tie formation and is a complete network analysis. This means that the ERGM estimation requires data on the network and attributes of both the spinout and its partner firms. Because logistic regression only estimates the spinout ego network, it requires data on the spinout network and attributes to estimate tie formation. Thus, ERGM is a better estimation method to analyze alliance tie formation. The ERGM results have to be interpreted similar to logistic regression results.

consider the set of all possible networks that could be formed and compare the set to the observed network. The ERGM is better suited to estimating network formation because it improves on logistic estimation, which tests one dyadic tie at a time. A comparison of ERGM estimation to logistic regression is explained below.

Let the network adjacency matrix be denoted as g. If node i and node j have a link, then $g_{ij} = 1$, otherwise $g_{ij} = 0$. By convention, a node cannot link to itself, so $g_{ii} = 0$. This is a standard way to organize data in the social network analysis literature. In my application, each firm is a node, with a set of characteristics that I collect in the matrix X, (e.g. firm age, resource diversity).

A logistic regression model would estimate the probability of a link between firm i and j as a function of the node characteristics

$$p(g_{ij} = 1|X) \qquad \forall i, j$$

where g_{ij} is the entry of the adjacency matrix and X is the set of firm characteristics. However, the logistic model assumes that each entry of the adjacency matrix is independent; that is, each link is formed independently. This assumption is quite strong in this study. Concretely, the assumption of independence means that if Firm 1 is considering whether to form a link to Firm 2, their decision is not affected by the links that Firm 1 had already formed in the past. If Firm 1 were forming the link to Firm 2 in search of higher resource diversity, the assumption of independence would be clearly violated. In addition, the assumption of independence also rules out that Firm 1's decision to form a link with Firm 2 does not depend on the network Firm 2 had created in the past. However, it is imaginable that Firm 1 will benefit differently from a link to Firm 2 when Firm 2 has a large, rather than small, alliance network. Therefore, it seemed useful to relax the assumption of independence for this study's specific application.

The ERGMs are statistical models that allow more flexible specification for network models, relaxing the assumption of independence of link formation (Snijders, 2002). The ERGM estimates the probability of a link between firms *i* and *j* conditional on the rest of the network and firm characteristics:

$$p(g_{ij} = 1 | g_{-ij}, X) \qquad \forall i, j$$

where g_{-ij} denotes the network adjacency matrix g excluding the link g_{ij} between firms *i* and *j*. This specification allows for dependence among links. For example, the decision of Firm 1 to connect to Firm 2 may depend on Firm 1's, as well as Firm 2's, existing networks.

The main concern in such a specification is that the conditional probability $p(g_{ij} = 1 | g_{-ij}, X)$ contains endogenous regressors, because links formed by pairs of firms other than *i* and *j* are decision variables and therefore endogenous. The main advantage of the ERGM specification is the ability to estimate the joint probability of the network adjacency matrix—that is, the joint probability of all the g_{ij} elements—and thus incorporate dependence between links in the estimation. The joint probability of all connections between firms is given by

$$P(g, X) = \frac{exp[\theta' t(g, X)]}{z(\theta)}$$

where θ is a vector of parameters and $t(g, X)$ is a vector of network statistics (the total number of links, the total number of triangles, the total number of links between firms in the same market, etc.). These statistics incorporate all the dependencies involved in network formation decisions between firms. The probability is known up to a normalizing constant, $z(\theta)$, which guarantees that P(g,X) is a proper probability. That is, it sums to 1 over all possible network realizations.

This model represents a probability distribution over all possible networks among *n* firms. Given a vector of parameters θ, one can compute which network of firms g is the most likely to occur among the $2^{\frac{n(n-1)}{2}}$ possible networks. Given an observed network g_{obs}, we can find the parameter estimate $\hat{\theta}_{mle}$ that maximizes the likelihood $P(g_{obs}|X;\theta)$. Given that the size of possible networks vastly outnumbers the parameters, estimating the probability of a network forming is computationally intensive, and requires Monte Carlo simulation methods.

Notice that the conditional model $p(g_{ij}=1|g_{-ij},X)$ is obtained from the joint likelihood as

$$p(g_{ij}=1|g_{-ij},X)=\frac{P(g,X)}{P(g_{-ij},X)}=\frac{P(g_{ij}=1,g_{-ij},X)}{P(g_{ij}=1,g_{-ij},X)+P(g_{ij}=0,g_{-ij},X)}$$

$$=\frac{\frac{exp[\theta' t(g_{ij}=1,g_{-ij},X)]}{z(\theta)}}{\frac{exp[\theta' t(g_{ij}=1,g_{-ij},X)]}{z(\theta)}+\frac{exp[\theta' t(g_{ij}=0,g_{-ij},X)]}{z(\theta)}}$$

$$=\frac{exp[\theta' t(g_{ij}=1,g_{-ij},X)]}{exp[\theta' t(g_{ij}=1,g_{-ij},X)]+exp[\theta' t(g_{ij}=0,g_{-ij},X)]}$$

$$=\frac{exp\left[\theta'[t(g_{ij}=1,g_{-ij},X)-t(g_{ij}=0,g_{-ij},X)]\right]}{1+exp\left[\theta'[t(g_{ij}=1,g_{-ij},X)-t(g_{ij}=0,g_{-ij},X)]\right]}=\frac{exp[\theta'\Delta t(g_{-ij},X)]}{1+exp[\theta'\Delta t(g_{-ij},X)]}$$

where $\Delta t(g_{-ij},X)$ is the change in the vector of network statistics generated when the additional link between firm *i* and *j* is formed.

The variables in this estimation method are in matrix format. The dependent matrix, the network of reported inter-firm ties, is created for all 1,182 firms. If two firms have a tie, 1 is entered in the matrix cell at the intersection of the focal firm's row and the partner's column; and 0 is entered otherwise (Ingram & Roberts, 2000). This matrix captures the formal ties formed by the spinout, which includes equity, nonequity, joint venture, and acquisition ties. Nonequity ties include collaboration or any other form of agreements. However, this matrix only captures the parent-spinout relationship that is established through some formal tie such as research, marketing, or commercial collaboration.

The second attributes matrix account for firm patents, technological distance, market distance, location, and degree centrality. This attributes matrix comprises the independent variables that determine the tie formation.

Results and Discussion

– –

Insert Figure 3 (Spinout Ego Network) here

– –

To visualize the formation of network ties among spinouts and other incumbents, I plot the spinout ego network as of 2011 (Figure 3). The spinouts represented by red dots are connected to the parent as well as nonparent firms. About 3% of the spinouts form a network tie with their parent. Only one spinout, Guidant Corp., forms an exclusive tie with the parent firm, Eli Lilly Corp.; it has 17 patents. In the graph, a black link represents a parent-spinout relationship; employees of the parent firm create the spinout. A red link represents strategic network ties with a nonparent firm. Few spinouts are more connected to incumbents, as clearly seen from the clustering in the top half of the graph. The graph shows that most spinouts are likely to form network ties with incumbent firms and, at times, with other spinouts. The spinouts that have more than five network ties has higher R&D output and products compared to other spinouts. One such firm is ICOS Corp., which had over 200 patents and six nonequity ties to nonparent incumbents. ICOS Corp. is in a similar product market as its parent firm, Amgen Inc. ICOS formed some nonequity ties, such as research collaborations with Glaxo SmithKline in 1994 and development and commercialization ties with Eli Lilly and Abbott Laboratories in 1998. These firms are competitors of ICOS's parent firm. This clearly shows that different spinouts have different strategies regarding the formation of network ties, which affects their performance or research output.

– –

Insert Table 3 (ERGM Estimation) here

– –

Table 3 shows the ERGM estimates for formation of alliance ties by spinouts. The table shows estimates for all four spinout categories; the comparison group is firms that did not establish ties. I control only for firm location and betweenness centrality, as this data is available for both the spinout and its partners. I do not control for firm age and size, as this information is not available for all the partner firms. In Table 3, I use a sample of 1,182 firms that includes parent firms, spinouts, and spinout partners. The parameters are estimated using simulation methods.[3] For each proposed parameter value, we simulate the probability of the observed network among the $2^{\frac{n(n-1)}{2}}$ possible networks where *n* is the number of firms (1,182). For each parameter value, I run the simulation for 100,000 iterations, and use standard diagnostics to check convergence of the estimates.[4]

The coefficients (Table 3) show that spinouts with similar technology and products as their parents (i.e., low technological and low market distance) prefer to form tie with firms that have no parent ties. The coefficient associated with spinouts with ties to firms that have indirect parent ties is positive and significant. However, this coefficient is lower than the one associated with firms that have no parent ties. These results suggest that spinouts that have low technology and low market distance with respect to the parent firm are likely to seek ties with firms that have no parent ties, lending support to Hypothesis 1c. Furthermore, I find no support for Hypotheses 1a or 1b.

The second categories of spinouts have different technology than their parent and enter a different market than their parents. For this category, the coefficients associated with forming ties with firms that have direct, indirect, and no ties to their parent are 0.413, 0.777, and -0.348, respectively. This result supports Hypothesis 2b, which states that spinouts with high technological and high market distances with respect to their parents are likely to form ties with firms that have indirect ties to their parent. Also, I do not find support for Hypotheses 2a or 2c.

---

[3] I use the package Bergm for the open-source statistical software R.

[4] The higher the number of iterations, the more precise the estimates. The trade-off is between precision and time for convergence. I experimented with different length of the simulations, to test the robustness of my results.

Finally, spinouts that have high technological and low market distances from their parent are more likely to form ties with firms that have direct ties to their parents. These results lend support to Hypothesis 3a and disprove Hypotheses 3b and 3c. These firms enter the parent market with new technology relative to their parent firms and pose a potential threat to parent technology. As a result, these firms are in a better bargaining position than other types of spinouts and are able to take advantage of their founders' prior affiliation to search for partners within firms that have direct parent ties.

Spinouts enter into alliance ties with other firms in order to gain access to resources. New firms have limited resources and enter the market with technology or product. However, their survival and success in high-technology industries is contingent on forging successful inter-organizational alliance ties to access complementary resources. Therefore, the next question is, what resources are transferred across these ties? Tables 4 and 5 show the multinomial logistic estimate that examines what resources are transferred across inter-organizational alliance ties. The key dependent variable captures three categories of resources, ranging from research, commercial, and marketing or funding resources. The marketing or funding resources category comprises manufacturing, marketing, and funding resources.

– –

Insert Table 4 (Resource Transfer-Direct and Indirect Ties) here

– –

– –

Insert Table 5 (Resource Transfer-No Ties) here

– –

New ventures have limited, crucial resources and want to protect them from misappropriation by their alliance partners. These new firms face a greater level of risk when they collaborate with firms that have either direct or indirect ties to their parent. Therefore, spinouts that choose to fulfill their need for resources with these firms are more likely to seek the resources for commercialization but avoid research ties that would allow their partner to access their core technology.

I find support for this conjecture for all types of spinouts (Table 4). Wald tests yielded chi-square values of 4342.58, 24.83, and 58.31 for research, commercial, and marketing or funding resources, respectively. All these values were statistically insignificant, suggesting that the coefficients of different types of spinouts are statistically different. As such, spinouts that seek ties with firms that have either direct or indirect ties to their parents access commercial resources through their alliance ties. Spinouts that form ties with firms that have direct or indirect parent ties are those that have different technology or operate in different product markets as their parents. Spinouts that are different from their parent in either technology or product market forged mostly commercialization ties. These results lend support to Hypothesis 4.

I analyze the resources transferred across ties with firms that have no parent ties using multinomial logistic regression (Table 5). Spinouts that have low market and low technological distances have the propensity to establish marketing, manufacturing, and funding ties. On the other hand, spinouts that have high technological and product market distances are more likely to establish research ties. Furthermore, spinouts that enter similar markets as their parent with a different technology relative to their parent are likely to establish marketing, manufacturing, and funding ties. Wald tests yielded chi-square values of 16.53, 113.71, and 32.88 for research, commercial, and marketing or funding resources, respectively. All these values are not statistically significant, suggesting that the coefficients of different types of spinouts are statistically different. In sum, spinouts that have similar technology and operate in similar markets as their parents are likely to establish marketing, manufacturing, or funding ties with firms that have no parent ties, supporting Hypothesis 5.

Robustness Checks: Multinomial Logistic Estimation for Spinout Alliance Formation

Prior research uses logistic regression to estimate the propensity to establish an alliance tie. Partners are categorized based on the presence or absence of ties to the parent firm. Therefore, I use multinomial logistic regression to estimate the spinout's propensity to form alliance ties with firms that have direct, indirect, or no ties to the parent. The coefficients generated by the multinomial logistic regression and ERGM cannot be compared directly, as the two methods are completely different in their underlying estimation methodology. The ERGM is better suited than multinomial logistic regression to estimating tie formation, as it accounts for correlation among ties (as explained in the methods section). However, it is possible to compare the findings from multinomial logistic regression to those from ERGM. In the case of conflict, ERGM results would be more reliable. The multinomial logistic regression also allowed me to control for spinout characteristics such as firm age and size (number of employees). This data is not available for the spinouts' partner firms. Hence, I did not incorporate it into the ERGM estimation.

The multinomial logistic regression results are shown in Tables 6 and 7. In Table 6, spinouts in the excluded category have low technological distance and high market distance from their parents. Table 6 shows that spinouts similar to their parent in both technology and product market (low technological and low market distances) are likely to form ties with firms that have no parent tie. This result supports Hypothesis 1c and yields a conclusion similar to the ERGM results.

– –

Insert Table 6 (Spinout Partner Choice-Excl hi-low) here

– –

– –

Insert Table 7 (Spinout Partner Choice-Excl lo-lo) here

– –

The second category is spinouts that have high technological and high market distances. These firms are not related to their parent technology or product market. I find that these spinouts are more likely to have ties to firms with indirect parent ties, supporting Hypothesis 2b. This result is similar to the finding from the ERGM estimates.

The final spinout category reported in Table 6 is firms that have high technological distance and low market distance from their parents. These firms enter the parents' product market using a different technology than their parents and are likely to develop ties with firms that have no parent ties. This result contradicts the ERGM prediction that these firms would form ties with firms that have direct parent ties. This discrepancy may be due to ERGM's ability to account for the underlying network structure that could shape tie formation. Therefore, the ERGM results are more reliable. Wald tests produced chi-square statistics of 7.28, 66.17, and 4.76, for ties to firms with direct, indirect, or no tie to the parent firm, respectively. Furthermore, the Wald test results were statistically insignificant, suggesting that the coefficients of the three spinout categories in this estimation are statistically different.

I perform additional analysis where I exclude spinouts with low market and technological distance from their parent (Table 7). Results in this table suggest that spinouts that have high market and high technological distances from their parents are likely to form ties with firms that have indirect ties to their parent. This further strengthens the findings from the previous multinomial logistic regressions and ERGM estimations for Hypotheses 2a-2c. I find that spinouts with high technological and low market distances from their parent are more likely to form ties with firms that have direct parent ties. These results contradict the multinomial logistic regression (Table 6) and concur with the ERGM results in (Table 3). For this case, I rely on the ERGM, instead of the multinomial logistic regression, results. Wald tests produced chi-square statistics of 8.97, 50.53, and 9.26 for firms with direct, indirect, or no ties to the parent firm, respectively. Furthermore, the Wald tests are statistically insignificant, suggesting that the coefficients of the three spinout categories are statistically different.

Conclusions

This chapter set out to examine the effects of a founder's prior employment in shaping the formation of a spinout's alliance network. A spinout inherits knowledge from its parent firm, but this knowledge inheritance comes with strings attached. The spinout does not become successful due to inheriting knowledge. Instead, it becomes successful based on how it uses this inherited knowledge in the market they enter. One such use of knowledge inheritance is to forge external relationships with other firms.

To understand the extent of the benefits from inheriting the parent's network, I classify the partner firms based on the presence or absence of their ties to parent firms. The three types of partner firms are firms that have direct, indirect, or no parent ties. I find that spinouts that have similar technology or are in similar product markets as their parents are likely to seek out partners with no parent ties. On the other hand, being different from their parents allows these spinouts to reap the benefits of their parents' networks by seeking firms that have either direct or indirect ties to the parents. Spinouts that have different technology and enter different markets from their parents forge ties with firms that have indirect ties to their parents. This suggests that spinouts fulfill their needs by forming ties with firms within their parents' networks. However, they deal with collaboration risk by distancing themselves from the parents' core network (parents' partners) and form ties with firms that have only indirect ties to the parents. These spinouts continue to face competitive pressure and collaboration risk from firms within their parents' networks. Finally, the spinouts that enter a similar product market with different technology from their parents' form ties with the parents' partners. These spinouts enter the parent market with a technology that could threaten the parents' products. This leverage aids the spinouts in negotiating alliance ties with firms that have direct ties to the parents.

Spinouts that forge ties with firms that have direct or indirect parent ties pursue only commercialization ties. The partners provide regulatory resources the spinouts need to enter the market. However, they shy away from forging research ties with these firms, because collaboration risk is too high in the early stages of technology development. Spinouts that seek partners with no parent ties are likely to seek manufacturing, marketing, or funding ties. These firms cannot leverage their founders' prior affiliation to scope out only partner firms that do not pose collaboration risk. One way to reduce this risk is to avoid research or commercialization ties that would allow partners to access the spinout's core technology. Spinouts that are different from their parents in terms of technology and/or product market form ties with firms that have direct or indirect parent ties—and these spinouts seek commercialization ties. Spinouts that have similar technology and operate in similar product markets, as their parents are the only firms that seek firms with no parent ties. These spinouts mostly forge marketing, manufacturing, or funding ties.

One of the challenges to understanding the relationship between a new venture's alliances and its founder's background lies in creation of the new firm. This study captures this role of new venture creation through the knowledge measure. Knowledge inheritance is the most common way to capture spinout creation, and I observe the knowledge that the firm received from the parent at its inception. This analysis is limited to firm-level controls; individual-level controls were not possible to analyze because the available data did not capture individual actions within the firm.

This paper makes three key contributions to new venture alliance and spinout literature. First, this study expands the resource perspective of new venture alliance formation by examining how young firms make strategic choices to seek resources through inter-organizational alliance ties. New ventures face greater collaboration risk and need to be very conscientious when seeking partners to fulfill their resource needs. Second, this study examines the influence of founders' social capital on external relationships established by new organizations. This connection is difficult to establish in prior studies because of the lack of data regarding new venture alliances and the founders' prior affiliations. The social capital accumulated by the founders' results from the pattern of contact networks those individuals experience. This study enhances understanding of how a founder's social capital translates to alliance networks at the firm level. Third, this study establishes that the influence of the unique historical conditions under which firms are created leads to a path-dependent process of network formation. In this study, the parent of the spinout firm continues to cast shadows on the post-spinoff relationships it forges.

A key implication of this study is the continued influence of the parent on the spinout's partner choices. Spinouts similar to their parents with respect to technology and product markets are likely to partner with firms with no parent ties. Spinouts that differs in both technology and product market are likely to engage in a local search for partners that have indirect ties to their parents. Only spinouts that enter the parent market with a technology different from their parents are likely to benefit from their parent network and seek partners with direct ties to their parent. Therefore, the manager of a new venture seeking alliance partners needs to be cognizant of the founder's background; and if the firm is a spinout, the manager needs to be aware of the potential collaborating risk from firms in the parent's network. However, spinouts seek only commercialization resources from partners with direct or indirect parent ties. Furthermore, they can deal with collaboration risk by screening potential partners or by forming ties that allow access to different types of resources. The best way seek partners and leverage the founders' social capital is to balance that collaboration risk with their resource needs.

Chapter 2: Effects of Founders' Background on Research, Alliances, and Performance: Employee and Academic Start-Ups

Introduction

New ventures have limited resources and thus benefit from their founders' pre-entry experience. The founding conditions of a start-up determine its ability to learn and adapt to the competitive environment in the long run (Cohen & Levinthal, 1990). The founders' pre-entry experience determines the resources endowed on the start-up and in turn shapes the founding conditions of the new venture. As a result, the heterogeneity in founders' background has an effect on the formation of firms' alliance ties, research output, and performance.

The literature on employee and academic entrepreneurship has looked independently at what determines the success of these new ventures. Firms founded by employee entrepreneurs benefit from their founders' industry experience (Agarwal et al., 2004; Chatterji, 2009), whereas academically founded firms benefit from having founders from prestigious universities (Shane, 2004). Few empirical studies have compared the performance of these two types of start-ups (Ensley & Hmieleski, 2005; Wennberg, Wiklund, & Wright, 2011; Winston Smith & Shah, 2013) or have examined the role of knowledge garnered by the founder's university education on the firm's performance (Wennberg et al., 2011). This study builds on the prior works by examining how the founders' backgrounds influence the alliance network, research output, and performance of academic and employee start-ups.

Employee start-ups are firms founded by individuals who have prior experience in the industry, and the prior employer of the employee entrepreneur is the parent firm. Academic start-ups are firms founded to commercialize a technology or idea developed within an academic institution, which may be a research laboratory or university. I use longitudinal data from start-ups in the pharmaceutical and medical device industry from 1986 to 2013 for this study. I find that employee start-ups are more likely to form alliance ties with other firms, and their alliance networks are larger than those of academic start-ups. However, employee start-ups tend to favor ties that allow them to access research and commercialization resources, as compared to academic start-ups that use their alliance ties to gain access to funding, marketing, and manufacturing resources. Additionally, academic start-ups are more likely to have a large number of patents. Furthermore, the founders' backgrounds do not determine the firms' IPO or acquisition. These results suggest that the founders' backgrounds shape the new ventures' initial choices regarding research output and alliance ties. However, the firm outcome results suggest that the founders' influence may be limited to shaping the paths the new ventures take, and has no affect on the firms' survival, IPO, failure, or acquisition.

Research Questions

Prior research has established that the founding conditions have a long-lasting effect on the performance of these new ventures. Parent firms are previous employers of the founders of employee start-ups. Successful parent firms generate successful employee start-ups (Agarwal et. al, 2004), while leading universities generate academic start-ups that are more likely to survive (Shane, 2004). Heterogeneity between these two types of start-ups arises from the process of new venture creation. These differences in their founding conditions shape their research output, alliance ties, and performance.

Employee start-ups are firms founded by employees of incumbent firms in the same industry (Agarwal et al., 2004; Klepper, 2002). Employee entrepreneurs use the technical and nontechnical knowledge inherited from their employers (Agarwal et al. 2004; Chatterji, 2009; Franco & Filson, 2006; Klepper & Sleeper, 2005). These new ventures have complementary assets relevant to the market of entry, since they enter markets related to their prior work experience (Phillips, 2002). Their entrepreneurial background determines their access to resources, and different founding conditions lead to heterogeneity in the knowledge within these new ventures (Agarwal & Shah, 2014). Employee start-ups can leverage their founders' industry experience to seek alliance partners.

The industry experience of founders of employee start-ups shapes the knowledge within the new venture (Agarwal et al., 2004). Employee entrepreneurs inherit technical knowledge through their founders' pre-entry experience (Agarwal et al., 2004; Chatterji, 2009; Klepper & Sleeper, 2005) and enter product markets similar to their parents' markets (Phillips, 2002). As a result, these start-ups are endowed with knowledge and resources relevant to the market of entry (Helfat & Lieberman), making them better at navigating the product market. Furthermore, they also gain nontechnical knowledge (Chatterji, 2009; Mitton, 1990; Stuart & Sorenson, 2003a; 2003b) and social capital through their founders' experience (Hallen, 2008; Roberts & Sterling, 2012).

Nontechnical knowledge includes downstream activities such as marketing, distribution, and overcoming regulatory barriers to commercialize their product. For example, Roberts and Sterling (2012) showed that employee start-ups in the Ontario wine industry leveraged their founders' industry experience, and social capital gained through their prior employer in the same industry, to create successful new ventures.

Employee entrepreneurship literature includes studies in different high-technology industries that are highly competitive, such as medical, laser, biotechnology, and semi-conductors (Chatterji, 2009; Ganco, 2013; Klepper & Sleeper, 2005; Stuart & Sorenson, 2003a; 2003b). Because these industries are highly competitive, employee entrepreneurs pursue the route of entrepreneurship mostly when they can protect their intellectual property through patenting (Ganco, 2013; Klepper & Sleeper, 2005). In these industries, technical knowledge plays a crucial role in the success of new firms; thus, new ventures use patents to protect their knowledge.

Academic start-ups evolve from universities with the intention of commercializing intellectual property developed within the university or research institution. Technical knowledge plays an important role in creating successful start-ups (Shane, 2004), and academic researchers gain this knowledge through their experience in academic institutions. Prior research in academic entrepreneurship has focused on start-ups from one or a few prestigious universities such as the Massachusetts Institute of Technology (Shane, 2004), the University of California (Lowe, 2002; Lowe & Zedonis, 2006), and universities in the United Kingdom (Lockett, Siegel, Wright, & Ensley, 2005; Vohora, Wright, & Lockett, 2004). The advantage of using this limited sampling frame was that these studies were able to disentangle the entrepreneurial process of firm formation. However, the authors were careful about generalizing these results for two reasons. First, these start-ups could be more successful than average academic start-ups due to their superior lineage. Second, the local environment, which may provide better availability of resources and opportunities, may have shaped the results of these studies.

Academic start-ups' knowledge is strongly related to the technology they develop in academic institutions. Most studies of academic start-ups were conducted in high-technology industries such as life sciences, biotechnology (Lowe, 2002; Shane, 2004; Stuart & Ding, 2006; Stuart, Ozdemir, & Ding, 2007), and science and engineering (Lockett & Wright, 2005; Vohora et al., 2004). Knowledge is crucial for success in these high-technology industries. However, these start-ups have limited industry experience. Their founding conditions endowed them with research- or technology-related resources, but their limited industry experience could affect their opportunities to form alliance ties.

Heterogeneity in Founders' Background and Endowment of Knowledge

New ventures benefit from their founders' pre-entry experience and knowledge. Employee entrepreneurship has focused on this knowledge in terms of technical and market know-how related to products and services (Agarwal et. al, 2004; Chatterji, 2009; Franco & Filson, 2006; Phillips, 2002). The literature on academic entrepreneurship has looked at this knowledge in terms of scientific discovery in academic institutions (Lowe & Zedonis, 2006; Shane, 2004). I combine these two literature streams to examine the effect of different founders' backgrounds on the firms' research output, alliance formation, and performance.

Employee start-ups are firms founded by employee entrepreneurs in the same industry as their parent firms or firms that are the prior employers of their founders.

Given the founders' experience in the same industry, employee start-ups are more likely to have relevant resources and knowledge for their market of entry. Employee start-ups leverage this technical and nontechnical knowledge to navigate the challenges in the market of entry, especially in their search for strategic alliance partners (see chapter 1). Academic start-ups are firms founded by academic entrepreneurs to commercialize a technology borne of innovation in an academic institution or university. These firms have little or no industry experience through their founders and may face difficulties navigating their product market and finding strategic alliance partners. In sum, employee start-ups are better equipped to deal with product market entry compared with academic start-ups.

Effect of Founders' Background on Formation of Alliance Ties

New ventures need complementary assets and knowledge relevant to the market of entry (Helfat & Lieberman, 2002). Inter-organizational relationships serve as a means for the focal firm to access critical resources outside the firm (Dyer & Singh, 1998). New ventures have limited resources, so establishing network ties reduces their risk related to firm survival. As a result, a new venture can improve its survival chances by securing relationships with key industry players. These network ties give access to knowledge, resources, and capabilities from the partners, which compensate for the disadvantage of the new venture's inexperience (Hite & Hesterly, 2001). As a result, forming ties with other firms increases the start-up's chance of survival through increased access to complementary resources (Pisano, 1990) and legitimacy, through association with successful firms (Baum & Oliver, 1991) and access to the partner firm's network.

The firm formation process shapes how new ventures go about seeking their alliance partners. Employee entrepreneurship portrays this process as formation predominantly through disagreements (Klepper, 2002; 2007), utilization of unexploited parent know-how (Agarwal et al., 2004), or imitating parent knowledge (Franco & Filson, 2006). This path of firm creation leads to competition between the parent and the employee start-up in the same product market, and the competition shapes the new venture alliance network (see chapter 1). On the other hand, academically founded firms are created in relatively collaborative environments; the university or academic institution fosters the academic start-up's process of commercializing the innovation. However, the start-up's limited industry experience limits its ability to find alliance partners.

Employee start-ups have experience in the same industry as their parents by virtue of their founders' pre-entry experience. Academic entrepreneurs create start-ups to develop early-stage research and need complementary assets to develop their technology. However, academic start-ups lack the industry experience that employee start-ups have through their founders' backgrounds. One implication of this stark difference in industry experience transpires in the form of alliance networks forged by these two start-up types. In addition, the differences in the founders' backgrounds could also drive the types of resources they seek. Hence, I explore the different types of resources transferred across each tie.

Differences in the alliance network size and types of resources can positively influence the firm's performance (Baum, Calabrese, & Silverman, 2000; Lavie, 2007; Powell, Koput, & Smith-Doerr, 1996). As firms increase their number of ties, they must pay attention to the alliance network composition to avoid redundant ties that provide access to the same information (Burt, 1992) or complementary capabilities (Gomes-Cassees, 1994). As the diversity of resources increases, it creates access to different resources and creates multiple sources of information for the focal firm. Each tie can transfer different types of resources. Therefore, diversity among these resources captures the strategic nature of tie formation. Efficient network composition consists of diverse resources (Baum et al., 2000), and this diversity enhances the firm's performance for two reasons. First, it increases the diversity of complementary resources that the focal firm can access. Second, it identifies whether the firm is forging ties that allow access to similar resources, and whether every tie increases access to new resources. Redundant ties could tax the focal firm by adding to the cost of collaboration without the additional benefit of accessing diverse, complementary resources. As resource diversity increases, the chance of the start-up's survival improves. Therefore, both the number of ties and the different types of resources transferred through these ties are crucial to understanding the effect of the founders' backgrounds on the alliance network configuration of these two start-up types. In the first question, I examine the propensity to form ties and the alliance network characteristics of both start-up types.

Question 1: Are employee start-ups more likely than academic start-up to aggressively seek alliance network ties with other firms? If so, how do the alliance network characteristics of employee start-ups differ from those of academic start-ups?

Effect of Founders' Backgrounds on Research Output

New ventures are endowed with resources through their founders' pre-entry experience. The resource endowment of a new venture at its founding is an important predictor of the knowledge within the firm and the strategic decisions it will make. These founding conditions have long-lasting effects on the firm's survival and success (Boeker 1989; Stinhcombe, 1965). However, because new firms are vulnerable to misappropriation of crucial resources by other firms in the industry, patenting would protect their knowledge. Additionally, firms with property rights have better bargaining positions than do firms that do not have patents.

Academically founded firms have research experience through their founders' pre-entry experience. Does this research experience translate into better research output than for employee start-ups? Academically founded firms benefit from their affiliation with their parent institution and leverage resources within the research institute to pursue their own research. Benefits of parent-institution affiliation include access to crucial resources such as the research facility, technology-transfer office, and infrastructure. The key characteristic of the knowledge pursued by these academic start-ups is that it is for novel technologies (Clarysse, Wright, & Van de Velde, 2011). These technologies are developed after creation of a new venture (Lowe & Zedonis, 2006). Therefore, the second question compares the research output of employee and academic start-ups.

Question 2: How does the patenting behavior of employee start-ups differ from that of academic start-ups?

Effect of Founders' Backgrounds on Firm Performance

New ventures have limited financial data, and thus firm survival is the most commonly used measure to evaluate a start-up's performance. Employee start-ups have relevant industry experience due to their founders' pre-entry experience. Using comprehensive longitudinal data of entrepreneurial firms in Sweden, Wennberg et al.

(2011) found that firms founded by employee entrepreneurs survived longer than and outperformed academic start-ups in terms of growth.

Another common measure of firm performance is IPO and acquisitions. Academic and employee start-ups are equally likely to go public (Audretsch & Stephan, 1996). Academic start-ups lack industry experience through their founders' pre-entry affiliation; thus, being acquired is a successful exit. Academic firms are very likely to be acquired by established firms (Lowe & Zedonis, 2006), even after IPO (Bonardo, Paleari, & Vismara, 2010).

Employee start-ups have relevant industry experience, whereas academic start-ups have research experience. Both types of new ventures need access to the right resources at the right time. Employee start-ups can leverage their founders' pre-entry experience to seek partners (chapter 1). Alternatively, they can generate patents to protect their knowledge. Academically founded firms could excel at this due to their founders' research experience. If the founders' backgrounds shape the research output and alliance ties of employee and academic start-ups, then does this influence extend to firm outcome? Firm outcome is captured as firm survival, IPO, acquisition, or failure. A better measure of firm performance is the detailed financial data of a firm's income and gross profit. However, only limited financial data is available for new ventures. Therefore, firm outcome is a good way to evaluate their performance. Hence, the final question that I examine is:

Question 3: How do employee start-ups perform relative to academic start-ups?

Data and Methods

Empirical Context

The pharmaceutical and medical device industry is a good empirical context to compare and contrast employee start-ups with academic start-ups for two reasons. First, this industry is highly competitive. Firms need both technology and alliance ties with other firms to be successful in this industry. Second, pharmaceuticals and medical devices are heavily regulated, making commercialization of the technology extremely challenging and expensive. One common way to deal with this competition is to form alliance ties with other firms to aid their research, commercialization, and marketing processes. Hence, both patents and alliance networks are essential features of their survival strategy and success, making this industry an ideal context to examine employee and academic start-ups.

Comparing employee start-ups with academics start-ups is extremely challenging because of the limited information available about the founding conditions of new firms. I deal with this challenge by developing a unique database, created by digitizing Medical Marketplace guides from 1986 to 2003. I use this Medical Marketplace database to identify the start-ups' origins and then construct a unique longitudinal dataset from 1986 to 2013 by combining data from different databases.

There are four key parts to the data collected: firm founding, patent information, alliance network, and financial data. First, information regarding the founders' backgrounds enables me to identify if an academic or an employee entrepreneur created the start-up. I use data from the Medical Marketplace database, along with data from LexisNexis and ThompsonOne, to establish the founding conditions of all the start-ups. I initially identify all 2,549 firms founded after 1986 from the Medical Marketplace database. I then track the founding team or information about the founding conditions.

New ventures are defined as employee start-ups when an incumbent firm in the industry previously employed a member of the new firm's top management team. During this classification process, I consider the employment history of the top management team only within five years of founding year for two reasons. First, the founder determines the top management team composition within its initial years of existence (Beckman & Burton, 2008). Moreover, in this industry, the core structure of the start-up's top management team usually remains the same for the first five years. Second, some firms were reported in these guides after five years from their founding date. Small firms are difficult to track, and few firms are tracked five years after their creation. In addition, the history of the firm is reported in detail, but the top management team is reported only for the current year. Most of the top management team has founders making this data very reliable. I also track the history of top management teams using ThompsonOne and LexisNexis database to identify employee start-ups.

Academic start-ups are firms founded to commercialize a technology developed within any research institution. I identify academic start-ups through the description of the firms' founding conditions and include all the firms founded by academic scientists or established to commercialize a technology developed within a research institute (e.g., a university or research organization). The final data contains 173 academic start-ups and 145 employee start-ups.

The second part of the data is related to innovation within the start-up and is captured by patent data collected from the Delphion database. The third component of the dataset is the alliance networks established by these start-ups. I use the Medical Marketplace database, SEC Filings, and LexisNexis to recover the alliance history for each start-up. Finally, I collect financial data from the Medical Marketplace database, SEC filings, COMPUSTAT, and additional firm-level characteristics like firm age, number of employees, location, and firm history from the Medical Marketplace database.

Variables

I test the above questions regarding the effect of the founders' backgrounds on the performance of start-ups using the data on employee and academic start-ups in the pharmaceutical and medical device industry. I analyze the effect of the founder' backgrounds on the research output, alliance network configuration, and firm outcome in terms of survival, IPO, failure, and acquisition.

Dependent and Independent Variables.

The key dependent variables are research output, alliance network configuration, and firm outcome. I capture the start-up's research output using patent data collected from the Delphion database. I measure the propensity to have patents using a dummy variable that takes a value of 1 when the firm has at least one patent at any time and a value of 0 otherwise. I also capture the quantity and quality of patents using the number of patents and the average citation of these patents, respectively. The patents quantity is measured using the total number of patents every year and the cumulative number of patents across all years. The average number of citations is captured as an average across all years and the five-year average citation is measured as the average number of citations within five years after the patent is granted.

The second set of dependent variables captures the alliance network configuration by measuring the total number of ties and resources transferred across each tie. The data on alliance ties is gathered from the Medical Marketplace database, LexisNexis, and SEC filings. I capture the propensity to form alliance ties with a dummy variable that has a value of 1 if the start-up had at least one alliance tie and a value of 0 otherwise.

To understand further how these start-ups leverage their alliance ties to gain access to different resources and partners, I create different measures to capture characteristics of the alliance network. The first characteristic is the size of the network, measured by the total number of ties. For the average number of resources transferred across each tie, I use four categories of resources: commercial, research, marketing or manufacturing, and funding. I measure the average number of resources transferred across each tie forged to capture the strength of a tie, because a firm with stronger alliance ties can access a greater variety of resources. I also measure the number of ties that transfer three specific types of resources: research, commercial, and marketing or funding. Each tie could transfer more than one resource; hence, the resource count does not directly match the number of ties. The research resource captures research and development, clinical trials, and anything related to technology development. The commercial resource captures commercialization, licensing, and regulatory related resources. The marketing and funding resources include marketing, sales, manufacturing, and funding-related resources. I then measure the diversity among the resources or partners in the new ventures' alliance networks, since having the same number of alliance ties does not mean the alliance network is structurally equivalent.

The concept of “structural equivalence” (Burt, 1992), wherein firms participating in similar businesses are considered homogenous in terms of skills, ties, and assets, has been used to justify the assumption that similar firms transfer similar resources across ties. Another implication of structural equivalence is that all resources between firms that form ties are readily accessible to both firms. This is not usually the case in the pharmaceutical and medical device industry, where patent rights are heavily protected and firms may work together on research projects. Hence, to understand which resources are being transferred across these ties and the differences across the partners, I create diversity measures related to the types of resources and partners.

The first measure relates to partner diversity. I use a Herfindahl index to measure the heterogeneity of partners. Partner diversity captures the extent to which the start-up can find diverse partners. In this study, the different types of alliance partners are universities, research labs, government intuitions, hospitals, and firms. I define partner diversity[5] as

$$PartnerDiversity_i = (1 - \sum_{ij} (PP_{ij})^2)/NT_i$$

where PP_{ij} is the proportion of resources received by start-up *i* through its alliance with partner *j*, and NT is start-up *i*’s total number of alliance ties to other firms. This value ranges from 0 to 1, and higher values indicate greater heterogeneity among the alliance partners.

---

5. The partner diversity measure is captured as network efficiency, or how efficient the start-up’s network is (Baum et. al, 2000). In this paper, both diversity measures merely capture the heterogeneity of resources or partners in a network.

The second measure is resource diversity, which captures the heterogeneity of resources transferred across each network tie, ranging from research to commercialization. The different types of resources are research, commercialization, manufacturing, marketing, and funding. This indicator measures which resources are transferred across all the ties that the focal firm creates. For example, a firm may invest in ten ties to gain access to research resources of the partner firms, or it may use four ties to access research resources and six ties to access marketing resources. The Medical Marketplace database allows me to examine all the resources transferred across the ties and to compute the diversity measure for the alliance network. Resource diversity is calculated using a Herfindahl index that varies from 0 to 1. A value of 1 indicates that the firm gains access to a diverse set of resources, whereas 0 indicates that the firm gains access to one type of resource. Higher values indicate more heterogeneity of resources. Resource diversity is measured as

$$ResourceDiversity_i = (1 - \sum_{ij} (PR_{ij})^2)/NT_i$$

where PR_{ij} is the proportion of resources received by start-up *i* through its alliance with partners *j*, and NT is start-up *i*'s total number of alliance ties to other firms. These two measures capture different types of diversity among types of partners and resources.

The final dependent variable, firmOutcome, captures the firm's outcome: survival, acquisition, IPO, or failure. This variable measures the economic performance of the start-up using firm outcomes rather than financial indicators such as net income or sales. Using firm outcome to capture start-up performance is standard practice in the literature (Chatterji, 2009), due to limited financial data available for small firms. The firm outcome data is consolidated using information from COMPUSTAT, the Medical

Marketplace database, SEC filings, and ventureXpert databases. I have limited financial data, such as gross profits, for some firms, and I include an analysis for this subsample in Tables 8 and 9. The skepticism associated with doing these regressions on gross profits, net income, and net sales is that this subsample includes start-ups that were relatively more successful.

The key independent variable is the start-up dummy that identifies whether the firm is an employee (value 1) or an academic (value 0) start-up.

Control Variables.

The control variables are the number of employees, total number of patents, total number of ties, firm age, and resource and partner diversity measures. Firm age is the number of years elapsed since the start-up's founding year. I control for firm age because new ventures' focus on technology and capability are expected to increase with time. The data comes from the Medical Marketplace database, which provides extensive information about how these start-ups are created. I also control for firm size by using the number of employees in the start-up every year. Bigger firms have more resources to devote to innovation and product commercialization, and thus perform better.

Firm location could allow them to access resources present in their local economy due to geographic agglomeration of firms within the same industry. As a result, being closer to countries with more innovation activities in the pharmaceutical and medical device industry may provide some benefits. Additionally, every country has its own regulations, and variations in these regulations may affect the start-up's performance. All variables and their definitions are listed in Table 8.

– –

Insert Table 8 (List of variables) here

_ _

Results and Discussion

Alliance Network Configuration

Employee start-ups have relevant industry experience, and they leverage this experience to seek alliance partners (chapter 1). Academic start-ups have limited industry experience, curtailing their opportunities to form alliance ties. The relevant industry experience of employee entrepreneurs could shape more than just alliance ties of these firms. More importantly, it could affect the types of products that these start-ups pursue. In this study, I focus only on alliance ties, as there is no consistent product-level data for these start-ups. There are three key issues with collecting such data. The first is that the FDA database captures only products approved in the United States. However, the new ventures in this study were from all parts of the world, making it challenging to collect detailed product-level data for all the firms. The second issue is that most firms listed only their latest product. The concern is that the first product introduced by this firm may not have shown up when I searched the FDA or company website for information. Third, the level of detail for each product may vary based on its importance to the firm, and there could be no consistent way to classify them. Therefore, I stuck to alliance network ties established by these firms as a way to capture how these new ventures leverage their founders' pre-entry experience in their markets of entry.

Founders affect the way start-ups forge their alliance networks. First, I examine the propensity of employee and academic start-ups to form at least one tie. I estimate the probability of establishing at least one tie using logistic regression. Table 9 shows that employee start-ups have a higher propensity to form alliances than do academic start-ups. Clearly, employee start-ups are eager to leverage their relevant industry experience to forge ties with other firms. If so, what sort of alliance ties do employee start-ups forge, compared with academic start-ups?

– –

Table 9 (Propensity to Form Alliances) here

– –

The next set of analyses digs deeper into the alliance network composition by examining the size of the alliance network and the resources transferred across these ties. Figure 4 clearly shows that there is a stark difference between the alliance networks forged by employee start-ups and academic start-ups. I capture the size of the alliance network by the total number of ties across all years. The second measure of alliance network characteristics is the average number of resources transferred across each tie the start-up formed. The measure of resources transferred across these ties is resource diversity, which captures different types of resources transferred across all ties. Additionally, I capture the heterogeneity among alliance partners using the partner diversity measure. I use random effects models for all these regressions. The key independent variable, start-up type, is time invariant; therefore, a random effects model is a better specification than a fixed effects model. The sign and significance of coefficients did not change between random effects and the firm fixed effects regression. However, a random effect is the better specification, as supported by the Hausman specification test.

– –

Insert Figure 4 (Number of Alliance) here

– –

Table 10 shows the estimated effect of the type of start-up on the network of the new venture. The dependent variables for this analysis are the total number of ties, the average number of resources transferred across each tie, resource diversity, and partner diversity (columns 1-4, respectively). I find that employee start-ups have larger networks than academic start-ups (column 1). I then examine the characteristics of these networks (columns 2-4). On average, employee start-ups gain access to more resources per tie (column 2) and have lower resource and partner diversity than do academic start-ups (columns 3-4). Although employee start-ups may access more resources with each tie, their overall network gains access to fewer types of resources and partners. Does this imply that employee and academic start-ups seek different types of resources?

– –

Insert Table 10 (Alliance Characteristics) here

– –

To understand why employee start-ups have lower resource diversity but higher average number of resources transferred across each tie than do academic start-ups, I examine which resources were transferred across these ties (Table 11). I group these resources into three categories: research, commercial, and marketing or funding ties. The dependent variables are the number of research, commercial, and marketing or funding ties (columns 1-3). The results suggest that employee start-ups are more likely to pursue research and commercialization resources, whereas academic start-ups are more likely to pursue marketing and funding resources. Furthermore, the availability of patents decreases the start-ups' propensity to pursue research resources and increases their propensity to pursue commercial, marketing, and funding resources.

– –

Insert Table 11 (Resource Transferred) here

– –

The propensity of employee entrepreneurs to form research ties supports the conjecture that these firms lack the research experience of academically founded firms. As a result, they seek out research resources to bolster their technological resources. Furthermore, they seek commercialization resources through their alliance ties. Conversely, academic start-ups lack commercialization resources, so forming alliance ties is a way to access these resources. However, academic start-ups may have less opportunity to form such ties than employee start-ups that can leverage their founders' pre-entry experience to seek alliance partners (chapter 1). Instead, academic start-ups form marketing, manufacturing, and funding ties. In sum, these results suggest that employee start-ups are able to navigate the market better than academic start-ups due to their founders' prior industry experience. In this case, employee start-ups are savvy in seeking out alliance partners and seem to fare better than do academic start-ups.

Research Output

Academic start-ups are created to commercialize a technology or innovation already developed within a university or academic institution. On the other hand, founders who want to pursue their ideas outside their current employment create employee start-ups. The subtle difference in the creation process could have a strong influence on the research output of these new ventures. I use patents to measure research output, since this captures the technological resources across both types of start-ups. Publications are another form of research output for academic start-ups, but not for employee start-ups. Therefore, I use patents to measure research output for both academic and employee start-ups. Research output is measured using three dependent variables: the firm has at least one patent, the total number of patents, and the average citations of these patents.

The first set of analyses examines the propensity of the firm to file for at least one patent and using logistic regression. Academic start-ups have extensive research experience due to their founders' prior employment at the academic institution where the technology was developed. When these firms are created, they file for patents to protect their competitive advantage—the technology developed at the academic institution. Employee start-ups do not have the flexibility to develop their technology using their parent firms' resources. As a result, they need to conduct the research upon creation of the new venture. These mechanisms are supported by the results displayed in Table 12, which shows that employee start-ups seem to have a lower propensity to file for patents. This suggests that academic start-ups are indeed more research productive than are employee start-ups, when patents capture research productivity.

– –

Insert Table 12 (Propensity to Patent) here

– –

The next question examines the volume and quality of patents of these two types of start-ups. All regressions are random effect models, as the key independent variable, start-up type, is time invariant. Results from both the random effects and firm fixed effects models have coefficients with similar sign and significance. Furthermore, the Hausman specification test shows that a random effects model is the better specification. The volume of patents filed by employee start-ups is considerably lower than by academic start-ups. The volume of patents is measured as the total number of patents held by the firm, and the total number of patents granted every year, as shown in columns 1 and 2, respectively, of Table 13. Both columns show that employee start-ups have far fewer patents compared to academic start-ups. Furthermore, having alliance ties to other firms increases the number of patents held by these start-ups. Columns 3 and 4 show the results of examining whether employee start-ups have higher quality patents. I measure patent quality using the average citation these patents received across all years and in a five-year window. According to this measure, the patents of employee start-ups are of lower quality than those of academic start-ups.

– –

Insert Table 13 (Patents- Quantity and Quality) here

– –

Firm Outcome: Survival, Acquisition, IPO, or Failure

Academic start-ups have additional research experience, but limited industry experience compared to employee start-ups. The limited industry experience of academically founded firms could have a detrimental effect on their survival and performance, whereas their additional research experience could endow them with technological resources crucial to their success and survival. On the other hand, employee start-ups can leverage their relevant industry experience to navigate the product market and succeed. Does this industry experience translate to better success and survival for employee start-ups? I measure the firm outcome of these start-ups using the multi-value dummy, firmOutcome, which takes values 0 to 3 for the firm's failure, IPO, acquisition, and survival, respectively.The base outcome for, in the dependent variable the multinomial logit is firm survival. The results of this regression are shown in Table 14.

– –
Insert Table 14 (Firm Outcomes) here
– –

Table 14 shows the results of two multinomial logistic regressions. Columns 1-3 show the results of the first multinomial logit, wherein one of the independent variables is the average number of resources transferred across each tie. The second multinomial logit results, tabulated in columns 4 and 5, include resource diversity as one of its independent variable. The average number of resources transferred across each tie captures the strength of each tie, whereas the diversity measure includes the different types of resources that a start-up gains access to through network ties. The multinomial logistic regression results for columns 1 and 4 suggest that employee start-ups are less likely to fail than academic start-ups. The coefficients of the employee start-up dummy for IPO and acquisition were not significant. The characteristics of ties, such as the strength of ties and diversity of resources, have a stronger effect on firm outcome than does just the start-up origin. The average number of resources transferred across each tie, and resource diversity have a negative effect on firm failure, IPO, or acquisition, as shown in columns 1-6.

I run additional analyses using gross profits, net income, and net sales as the dependent variables (Tables 15 and 16). The results in Table 15 suggest that employee start-ups are likely to make lower profit (column 1) and income (column 3) compared to academic start-ups. However, these results did not hold when I control for firm heterogeneity using firm fixed effects (Table 16). Financial data is available for start-ups that were relatively successful and report their performance. Thus, I cannot interpret these findings as definitive evidence. Hence, I conclude that firm outcomes are a good representation of firm performance. Table 17 and Figure 5 show the survival functions of both types of start-ups going public (i.e., IPO). This only looked at firms' IPOs and use Breslow's approximation for the hazard function. The results suggest that employee start-ups are more likely than academic start-ups to go public. However, the results can be best interpreted when all the alternative outcomes are considered in competing risk models. Such estimation needs data like the time of firm acquisition or bankruptcy, which would entail further data collection. Hence, only the event history analysis of firm IPO is included in this study for now. Overall, I find that the founders' backgrounds have little or no impact on firm performance.

– –

Insert Figure 5 (Survival function) here

– –

– –

Insert Table 15 (OLS Regression) here

– –

– –
Insert Table 16 (Firm FE Regression) here
– –

– –
Insert Table 17 (Cox Model) here
– –

Conclusions

This chapter set out to study the differential impact of start-up founders' background on the formation of alliance ties, research output, and firm performance of employee and academic start-ups. The academic start-up has better research resources by virtue of its founder's experience in the research institution. On the other hand, the employee start-up has relevant industry experience, allowing it to deal with a highly competitive environment. I find that academic start-ups have a higher research output compared with employee start-ups. This finding supports the proposition that academic founders endow the start-up with better research resources than employee startups. Additionally, compared to academic start-ups, employee start-ups are more prolific in forming alliance ties with other firms. This finding lends supports to the inference that the employee start-ups benefit from their founders' industry experience.

The alliance network composition of these start-ups suggests that employee start-ups leverage their industry experience to forge ties with other firms. However, they lack the research experience that academic start-ups have and thus seek research or commercial ties with other firms. Academic start-ups have research experience but limited industry experience. This would indicate that they would seek commercialization resources. However, their lack of relevant industry experience proves detrimental to their ability to seek commercial ties. Instead, they form marketing, manufacturing, and funding ties with other firms. Research experience of the academic start-ups has a positive impact on the volume of patents they generate. Furthermore, these start-ups produce higher quality patents than do employee start-ups.

The effect of the founders' backgrounds on firm performance is not as evident, suggesting that the founders' pre-entry experience shapes their preliminary choices, such as patents and alliance ties. However, heterogeneity in the founder's background does not completely determine a start-up's success or failure. This result contradicts prior research that compared employee and academic start-ups to find that employee start-ups fared better in industry (Wennberg et al., 2011) due to their founders' pre-entry experience.

The founders' backgrounds may not have any impact on the start-ups' performance for two reasons. First, prior studies did not look at both technology and alliance ties to examine the effect of founders' backgrounds on firm performance. The founders' backgrounds may shape initial choices related to technology and alliance network, but their pre-entry experience may have no bearing on firm performance. Examining the paths traversed by these new ventures, instead of comparing their performance, may have driven the results in the previous studies.

Second, the sampling frames of this study differed from earlier studies. Prior studies compared employee and academic start-ups using different sampling contexts, such as start-ups in Sweden (Wennberg et al., 2011) or start-ups from three southeastern U.S. universities matched with non-university start-ups (Ensley & Hmieleski, 2005). Instead, in this study I compare start-ups in the pharmaceutical and medical device industry from the United States, Europe, and Asia. Furthermore, I sample the employee and academic start-ups from the Medical Marketplace database. These different sampling frames could create some limitations when directly comparing the studies. However, the non-result is an interesting finding, as it suggests that the founders' backgrounds shape the paths traversed by these start-ups but do not determine firm performance.

These results have implications for both theory and practice. With respect to theory, this study adds to the understanding of how founders could leave an imprint on the alliance network and research output of these new ventures. However, differences in founders' pre-entry experience do not affect the firm performance. In practice, entrepreneurs could learn how to leverage their experience to benefit the firms' knowledge and network. Furthermore, this study encourages founders to focus on imminent strategic decisions pertaining to knowledge creation and potential alliance partners. Founders can leverage their experience to fulfill their resource needs by either developing or patenting the knowledge within the firm. Alternatively, they can fulfill the need for these resources by forming alliance ties. These strategic decisions, rather than the lack of resources at its founding, seem to shape the firm's outcome. In conclusion, the founder's background does not determine firm performance. Instead, it just shapes the path to success or survival taken by the start-up.

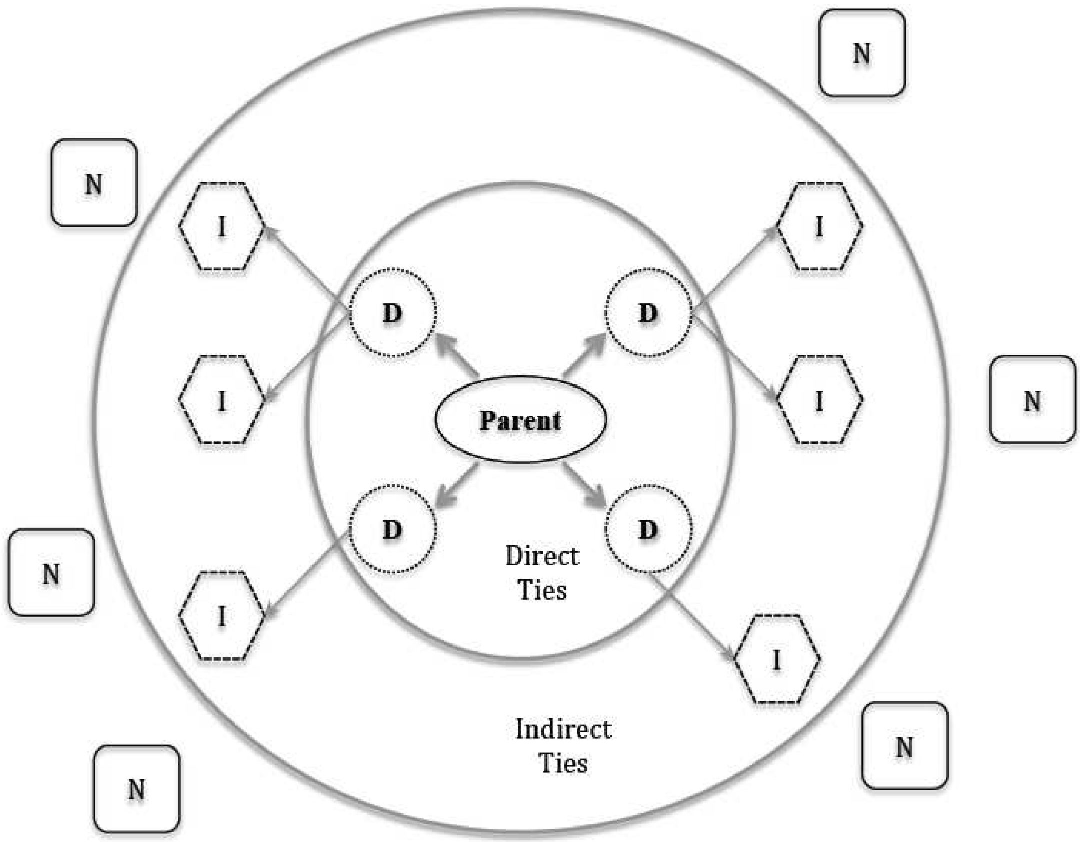
Appendix - Tables and Figures

Figure 1. Spinout Categories based on Technological and Market Distance from their Parent

		Market Distance	
		High	Low
Technological Distance	High	Apply different knowledge for a different product	Apply different knowledge for a similar product
	Low	Apply similar knowledge for a different product	Apply similar knowledge for a similar product

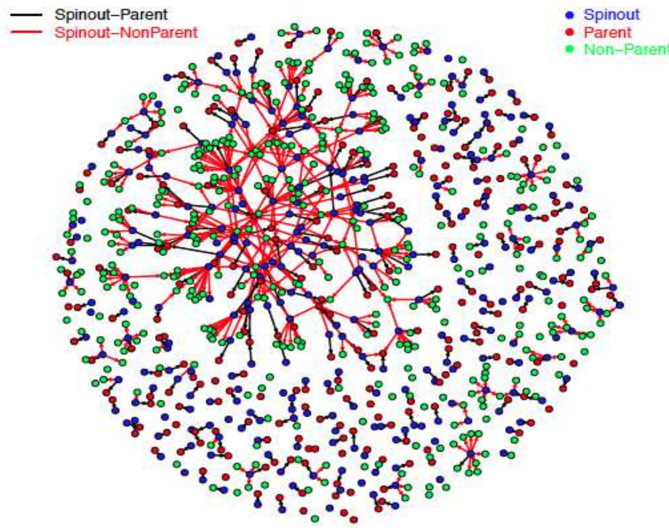
This figure shows the categorization of spinouts based on the technological and market distance relative to their parents. Each quadrant explains how the spinout applies the knowledge it inherited from the parent in different product markets relative to its parent's product market.

Figure 2. Partner Types



This figure shows the three types of partner firms based on their network relationships with the parent firm. Firms denoted as "D" have direct ties to and are partners of the parent. Firms with indirect ties to the parent or are partners of a parent's partner are represented as "I." Finally, firms listed as "N" are firms with no ties—neither direct nor indirect—to the parent firm.

Figure 3. Spinout Ego Network (2012)



This graph shows the spinout ego network. The spinouts are represented by red dots. A black link represents a spinout-parent relationship: the employees of the parent firm create the spinout. A red link represents formal network ties between a spinout and a nonparent firm. The spinout-parent tie shows that the firm spun out from the respective parent firm, whereas a spinout-nonparent tie represents an actual alliance established between the two firms. Less than 3% of spinouts form ties with their parents. Hence, those ties were not plotted on this network map.

Table 1. Variables Definitions

Variable	Definition
Dependent Variables	
Parent alliance network	Firms that have direct or indirect ties to the parent firm
Partner type	Firms with direct ties to the parent or are the parent's partners, or firms with indirect ties to the parent through a tie to a parent's partner
Resource type	Resource transferred across a tie, such as research, commercial, manufacturing, or marketing.
Independent Variables (by Spinout Type)	
Low Market and Low Tech Distance	Spinouts with low technological and market distances from their parents
High Market and High Tech Distance	Spinouts with high technological and market distances from their parents
High Market and Low Tech Distance	Spinouts with high technological and low market distance from their parents
Low Market and Low Tech Distance	Spinouts with low technological and low market distance from their parent
Control Variables	
Total ties	Number of ties formed by spinout, parent, and partner firms as of 2012
Location	Address of the parent, partner, and spinout; used to create dummies for the countries
Spinout age	Number of years since its founding date
Spinout size	Number of employees within a firm
Patent	Number of patents or patent dummy for spinout, parent, and partner s

This table describes key variables used in the study.

Table 2. Descriptive Statistics and Correlation Matrix

Variables	*Mean*	*SD*	Min	Max	1	2	3	4	5	6	7	8
1. Spinout: M^{Low} & T^{Low}	0.571	0.495	0	1	1							
2. Spinout: M^{High} & T^{High}	0.058	0.233	0	1	-0.29	1						
3. Spinout: M^{Low} & T^{High}	0.246	0.431	0	1	-0.66	-0.14	1					
4. Spinout: M^{High} & T^{Low}	0.117	0.322	0	1	-0.42	-0.09	-0.21	1				
5. Firm Age	22.028	7.513	4	109	0.14	-0.09	0.01	-0.16	1			
6. #Employees	406.842	1421.955	2	13000	0.06	-0.03	-0.01	-0.05	0.18	1		
7. # Patents	48.417	88.437	0	500	-0.09	0.08	0.11	-0.05	-0.02	0.21	1	
8. Spinout Betweenness Centrality	13937.574	30928.149	0	2.78E+05	0.07	0.08	-0.11	-0.02	0	0.27	0.33	1

This table lists the mean, standard deviation, and minimum and maximum values, along with correlations for all variables, in columns 1-8. Columns 1-8 are variables listed in the first column titled “Variables,” These statistics are calculated for 235 spinouts from 1986 to 2012.

Table 3. ERGM Estimation of Formation of Alliances Ties by Spinouts

Variable	Estimate
Spinout: M^{Low} & T^{Low}	0.634^{***} (0.483)
Spinout: M^{Low} & T^{High}	-0.143^{***} (0.175)
Spinout: M^{High} & T^{High}	0.362^{***} (0.413)
Parent Direct Partner	-0.562^{***} (1.096)
Parent Indirect Partner	-0.980^{***} (1.641)
Nonparent Network	-4.446^{***} (1.641)
Spinout: M^{Low} & T^{Low} *Parent Direct Partner	-0.132^{***} (0.360)
Spinout: M^{Low} & T^{Low} *Parent Indirect Partner	0.109^{***} (0.201)
Spinout: M^{Low} & T^{Low} *Nonparent Network	0.690^{***} (0.309)
Spinout: M^{Low} & T^{High} *Parent Direct Partner	1.005^{***} (0.219)
Spinout: M^{Low} & T^{High} *Parent Indirect Partner	-0.547^{***} (0.311)
Spinout: M^{Low} & T^{High} *Nonparent Network	0.0791^{***} (0.506)
Spinout: M^{High} & T^{High} *Parent Direct Partner	0.413^{***} (0.413)
Spinout: M^{High} & T^{High} *Parent Indirect Partner	0.777^{***} (0.370)
Spinout: M^{High} & T^{High} *Nonparent Network	-0.348^{***} (0.175)
Degree Centrality	0.0033^{***} (0.002)
Country US	0.197^{***} (0.127)

This table tabulates the results of the ERGM estimation with 100,000 iterations for 1,182 firms (N= 1182). These firms include spinouts, parents, and partners. The ERGM estimation accounts for network and characteristics of all the firms while predicting the formation of alliance ties. The M and T in the spinout categories represent product market and technological distance. The excluded category has spinouts with high market distance and low technological distance.

Notes. Standard errors in parentheses
$^{*}p < 0.05$
$^{**}p < 0.01$
$^{***}p < 0.001$

Table 4. Resource Transfer across Ties—Firms with Direct or Indirect Parent Ties

	(1)	(2)	(3)
	Research	Commercial	Marketing & Funding
Spinout: M^{Low} & T^{Low}	-0.613	14.017***	-1.676***
	(0.489)	(0.518)	(0.400)
Spinout: M^{High} & T^{High}	-1.254	15.813***	0.431
	(0.661)	(0.498)	(0.377)
Spinout: M^{Low} & T^{High}	-16.215***	15.098***	0.404
	(0.362)	(0.476)	(0.358)
Spinout Age	0.009	0.062***	0.068***
	(0.031)	(0.012)	(0.011)
#Employees	-0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)
Country: USA	-1.070	-0.598	-1.394***
	(0.576)	(0.399)	(0.263)
Parent Patent Dummy	15.181***	-2.687***	-1.903***
	(0.554)	(0.168)	(0.185)
Partner Patent Dummy	-0.713	3.391***	2.824***
	(0.375)	(0.373)	(0.264)
Constant	-18.289***	-20.921***	-4.946***
	(0.536)	(0.580)	(0.494)
Observations	7,585	7,585	7,585
ll	-1651.450	-1651.450	-1651.450
df_m	22.000	22.000	22.000
aic	3352.900	3352.900	3352.900
bic	3526.248	3526.248	3526.248

The dependent variable is a dummy variable that takes the value of 1 for a research tie, 2 for a commercial tie, 3 for a manufacturing, marketing, or funding tie, and 0 otherwise. Columns (1), (2), and (3) tabulate the results of multinomial logistic regression for the propensity to form ties to access research, commercial, or marketing and funding resources. Marketing and funding represents manufacturing, marketing, and funding resources. The M and T in the spinout category represent product market and technological distance, respectively. This estimation is for a sample of partners with direct or indirect ties to their parents.

Notes. Standard errors in parentheses
$^{*}p < 0.05$
$^{**}p < 0.01$
$^{***}p < 0.001$

Table 5. Resources Transfer across Ties to Firms with No Parent Ties

	(1)	(2)	(3)
	Research	Commercial	Marketing & Funding
Spinout: M^{Low} & T^{Low}	0.555**	0.259*	0.793***
	(0.191)	(0.124)	(0.193)
Spinout: M^{High} & T^{High}	1.218***	0.252	0.047
	(0.230)	(0.192)	(0.335)
Spinout: M^{Low} & T^{High}	0.738***	0.941***	1.221***
	(0.198)	(0.122)	(0.200)
Spinout Age	-0.018***	-0.015***	0.004
	(0.005)	(0.003)	(0.003)
#Employees	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Country: US	0.216	0.965***	-0.137
	(0.141)	(0.134)	(0.114)
Parent Patent Dummy	-0.309***	-0.419***	0.019
	(0.091)	(0.061)	(0.088)
Partner Patent Dummy	2.096***	3.374***	2.570***
	(0.094)	(0.085)	(0.094)
Constant	-8.336***	-9.035***	-9.058***
	(0.217)	(0.188)	(0.203)
Observations	724,635	724,635	724,635
ll	-1.35e+04	-1.35e+04	-1.35e+04
df_m	24.000	24.000	24.000
aic	27023.059	27023.059	27023.059
bic	27333.382	27333.382	27333.382

The dependent variable is a dummy variable that takes the value of 1 for research ties; 2 for commercial ties; 3 for manufacturing, marketing, or funding ties; and 0 otherwise. Columns (1), (2), and (3) tabulate the results of multinomial logistic regression for the propensity to form ties to access research, commercial, or marketing and funding resources. The marketing and funding represents manufacturing, marketing, and funding resources. The M and T in the spinout categories represent product market and technological distance, respectively. This estimation is for a sample of partners with no parent ties.

Notes. Standard errors in parentheses
$^{*}p < 0.05$
$^{**}p < 0.01$
$^{***}p < 0.001$

Table 6. Spinout Partner Choice among Firms with Direct, Indirect, or No Ties to the Parent (Multinomial Logit), Excluding M^{High} & T^{Low}

	(1)	(2)	(3)
	Direct	Indirect	Nonparent
Spinout: M^{Low} & T^{Low}	-0.118	0.103	0.456*
	(0.113)	(0.093)	(0.224)
Spinout: M^{High} & T^{High}	0.183	0.960***	0.728
	(0.166)	(0.151)	(0.388)
Spinout: M^{Low} & T^{High}	0.676*	0.855***	0.943*
	(0.263)	(0.156)	(0.404)
Spinout Age	0.004	-0.005	-0.007
	(0.004)	(0.005)	(0.005)
#Employees	0.000	0.000*	0.000***
	(0.000)	(0.000)	(0.000)
Country: US	-0.049	-0.032	0.433
	(0.280)	(0.097)	(0.252)
Parent Betweenness Centrality	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Partner Betweenness Centrality	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Constant	-6.298***	-5.529***	-6.948***
	(0.266)	(0.156)	(0.346)
Observations	732,220	732,220	732,220
ll	-5.73e+04	-5.73e+04	-5.73e+04
df_m	24.000	24.000	24.000
aic	1.15e+05	1.15e+05	1.15e+05
bic	1.15e+05	1.15e+05	1.15e+05

The dependent variable is a dummy variable that takes the value of 1 for firms with direct ties to the parent firm, 2 for firms with indirect ties to parents, 3 for firms outside the parent network, and 0 otherwise. Columns (1), (2), and (3) tabulate the results of multinomial logistic regression for the propensity to form ties to firms with direct, indirect, and no ties to their parent firms. The M and T in the spinout categories represent product market and technological distance, respectively. The excluded spinout category is firms that have low technological and high market distance from their parents.

Notes. Standard errors in parentheses
$^{*}p < 0.05$
$^{**}p < 0.01$
$^{***}p < 0.001$

Table 7. Spinout Partner Choice among Firms with Direct, Indirect, or No Ties to the Parent (Multinomial Logit), Excluding M^{Low} & T^{Low}

	(1)	(2)	(3)
	Direct	Indirect	Nonparent
Spinout: M^{High} & T^{High}	0.255	0.871***	0.262
	(0.177)	(0.130)	(0.225)
Spinout: M^{Low} & T^{High}	0.755**	0.739***	0.471
	(0.279)	(0.133)	(0.337)
Spinout: M^{High} & T^{Low}	-0.083	-0.166	-0.556**
	(0.163)	(0.092)	(0.215)
Spinout Age	0.003	-0.004	-0.008
	(0.004)	(0.005)	(0.005)
#Employees	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)
Country: US	-0.051	-0.036	0.432
	(0.283)	(0.098)	(0.253)
Parent Betweenness Centrality	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Partner Betweenness Centrality	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Constant	-6.352***	-5.417***	-6.457***
	(0.320)	(0.153)	(0.243)
Observations	732,220	732,220	732,220
ll	-5.73e+04	-5.73e+04	-5.73e+04
df_m	24.000	24.000	24.000
aic	1.15e+05	1.15e+05	1.15e+05
bic	1.15e+05	1.15e+05	1.15e+05

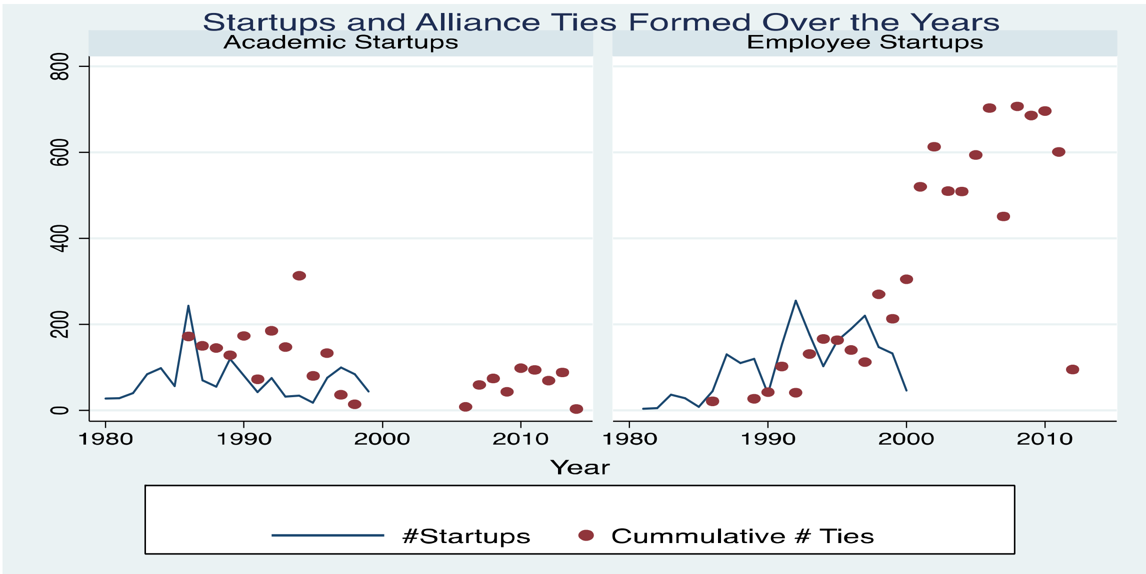
The dependent variable is a dummy variable that takes the value of 1 for firms with direct ties to the parent firm, 2 for firms with indirect ties to the parent, 3 for firms outside the parent network, and 0 otherwise. Columns (1), (2), and (3) tabulate the results of multinomial logistic regression for the propensity to form ties to firms with direct, indirect, and no ties to their parent firms. The M and T in the spinout categories represent product market and technological distance, respectively. The excluded spinout category is firms that have low market and low technological distance from their parents.

Notes. Standard errors in parentheses
$^{*}p < 0.05$
$^{**}p < 0.01$
$^{***}p < 0.001$

Table 8. List of Variables, Their Definitions, and What They Measure

Variable	Definition	Measures
Dependent Variables		
Has alliance ties (Dummy variables)	Dummy, captures if the firm has at least one alliance	Propensity to form alliance ties
#Ties	Total number of ties forged by the start-up	Size of their alliance
Resource diversity	Herfindahl index type measure, captures types of resources transferred across all ties	Heterogeneity among resources access through alliance network
Partner diversity	Herfindahl index type measure, captures types of alliance partners	Heterogeneity among alliance partners
#Research ties	Number of ties used to access research resources	Propensity to seek research resources
#Commercial ties	Number of ties used to access commercialization resources	Propensity to seek commercialization resources
#Market &funding ties	Number of ties used to access marketing, manufacturing, and funding resources	Propensity to seek marketing, manufacturing, and funding resources
Has patent	Dummy, captures if the firm has a patent	Propensity to patent
#Patents every year	Number of patents granted to the firm every year	Research output every year
#Patents	Total number of patents	Overall research output
Avg #Citations	Average number of patent citations , all years	Quality of patents in the start-up
Avg #Citations (5-year)	Average number of patent citations in 5 years	Quality of patents in the start-up
Gross profit, Net sales, Net income	Profit, net sales, and net income made by the start-up - data is available only for a sub-sample	Firm performance measured using financial data
Firm outcome	If the firm survives, fails, is acquired, or goes IPO	Firm performance measured by outcome
Independent Variable		
Start-up type	Dummy, captures if firm is an academic or employee start-up	Heterogeneity of founders' background
Control Variables		
Firm age	Number of years since the firm's founding	Years of experience
Firm location	Dummy, captures if firm is located in Asia (includes Australia), North America, or Europe	Location could shape opportunities
Firm size	Number of employees	Larger start-ups may have more resources

Figure 4. Comparison of Alliance Ties Formed by Academic and Employee Start-ups



This graph shows the difference between the ties forged by academic start-ups and those forged by employee start-ups. The blue line represents the number of start-ups created every year and stops at 2003 because the Medical Marketplace database contained data only to 2003.

Table 9. Start-up Propensity to Form Alliance (Logit)

Variable	Has Alliance Ties
Employee start-up	0.339** (0.111)
#Patents	0.00131*** (0.000263)
Firm Age	-0.000398 (0.00474)
#Employees	-0.0000495*** (0.0000144)
USA	1.669 *** (0.365)
Year controls	Y**
Constant	-3.458** (1.171)
Observations	3,105

This is a logistic regression where the dependent variable is a dummy that takes the value 1 if the start-up has at least one alliance tie to other firms, and the value 0 otherwise.

Notes. Standard errors in parentheses
$^{*}p < .05$
$^{**}p < .01$
$^{***}p < .001$

Table 10. Start-up Alliance Network Characteristics (Random Effects)

	(1)	(2)	(3)	(4)
	# Ties	Average # Resources per Tie	Resource Diversity	Partner Diversity
Employee start-up	0.0782* (0.0314)	0.0587*** (0.00152)	-0.169*** (0.00499)	-0.0390*** (0.000602)
Firm age	-0.000403 (0.00119)	-0.0000816 (0.0000579)	-0.0000164 (0.000190)	-0.0000442 (0.0000229)
#Patents every year	0.00135*** (0.000233)	0.0000349** (0.0000114)	-0.000123** (0.0000379)	0.00000271 (0.00000449)
#Employees	-0.000000289 (0.00000188)	-2.47e-08 (9.14e-08)	6.07e-08 (0.000000304)	-8.20e-09 (3.61e-08)
USA	-0.00150 (0.0227)	-0.0000583 (0.00110)	0.000772 (0.00368)	-0.0000240 (0.000436)
Year controls	Y	Y	Y	Y
Constant	2.782*** (0.226)	0.102*** (0.00718)	0.210*** (0.0122)	0.0387*** (0.00286)
Observations	3,105	3,105	3,105	3,105

All regressions of random effects, where the dependent variables from column 1-4 are number of ties, average number of resources transferred across each tie, resource diversity, and partner diversity

Notes. Standard errors in parentheses
* $p < .05$
** $p < .01$
*** $p < .001$

Table 11. Resources Transferred through Alliance Ties (Random Effects)

	(1)	(2)	(3)
	#Research Ties	#Commercial Ties	#Marketing & Funding Ties
Employee start-up	1.289*** (0.0236)	0.474*** (0.0465)	-0.949*** (0.0157)
Firm age	-0.00118 (0.000895)	-0.000446 (0.00177)	-0.000411 (0.000598)
#Patents every year	-0.00118*** (0.000176)	0.00229*** (0.000353)	0.000683*** (0.000118)
#Employees	-6.07e-08 (0.00000141)	-0.000000517 (0.00000283)	-0.000000121 (0.000000946)
USA	0.000988 (0.0170)	-0.000247 (0.0342)	-0.000455 (0.0114)
Year controls	Y	Y	Y
Constant	0.764*** (0.138)	0.697*** (0.117)	1.039*** (0.0686)
Observations	3,105	3,105	3,105

All regressions of random effects, where the dependent variables from column 1-3 are number of research, commercial, and marketing/funding ties

Notes. Standard errors in parentheses
$^{*}p < .05$
$^{**}p < .01$
$^{***}p < .001$

Table 12. Propensity of Start-ups to Patent (Logit)

	(1)
Employee start-up	-1.201^{***} (0.118)
Firm age	-0.0126^{**} (0.00472)
#Employees	0.0000460^{***} (0.00000885)
#Ties	0.0467^{***} (0.00820)
USA	0.468 (0.277)
Year controls	Y
Constant	-1.028 (1.218)
Observations	3,105

This is a logistic regression where the dependent variable is a dummy that takes the value 1 if the start-up has at least one patent and the value 0, otherwise.

Notes. Standard errors in parentheses
$^{*}p < .05$
$^{**}p < .01$
$^{***}p < .001$

Table 13. Volume and Quality of Patents within Start-ups (Random Effects)

	(1)	(2)	(3)	(4)
	#Patents	#Patents Every Year	Avg Citations	Avg Citations (5-yr)
Employee start-up	-94.60*** (4.377)	-4.225*** (0.658)	-8.036*** (0.770)	-8.335*** (1.654)
Firm age	0.229 (0.224)	0.0651* (0.0290)	0.0213 (0.0380)	0.0281 (0.0734)
#Employees	0.0000377 (0.000356)	0.000208** (0.0000677)	-0.000119 (0.0000674)	-0.0000155 (0.000171)
#Ties	29.46*** (1.796)	0.317*** (0.0656)	0.338* (0.159)	0.460** (0.169)
USA	-0.853 (4.302)	0.0275 (1.278)	0.258 (0.842)	4.381 (3.117)
Year control	Y**	Y*	Y**	Y*
Constant	40.60* (16.69)	3.841* (1.499)	6.737*** (1.275)	10.82** (3.638)
Observations	3,105	3,105	3,105	3,105

Tabulation of all random effects regression; the dependent variables are total number of patents, number of patents every year, average citations per patent, and average citation in a 5-year window for the start-up

Notes. Standard errors in parentheses
*$p < .05$
**$p < .01$
***$p < .001$

Table 14. Firm Outcomes of Employee and Academic Start-ups (MLogit)

	(1)	(2)	(3)	(4)	(5)	(6)
Firm outcome	Failure	IPO	Acquisition	Failure	IPO	Acquisition
Employee start-up	-1.174* (0.494)	-0.151 (0.141)	0.610 (0.359)	-1.141* (0.482)	-0.167 (0.141)	0.484 (0.355)
Firm age	-0.123** (0.0405)	0.0287*** (0.00841)	-0.0896*** (0.0236)	-0.120** (0.0403)	0.0301*** (0.00870)	-0.0895*** (0.0237)
USA	14.35 (1092.2)	0.829** (0.316)	14.37 (764.4)	16.35 (2796.5)	0.765* (0.334)	16.05 (1894.3)
#Patents	-0.103* (0.0428)	0.00383*** (0.000967)	0.00586*** (0.00101)	-0.0993* (0.0415)	0.00316*** (0.000914)	0.00530*** (0.000963)
#Ties	0.209*** (0.0483)	0.0436* (0.0172)	0.0140 (0.0420)	0.130** (0.0419)	-0.0253 (0.0146)	-0.0958** (0.0365)
Average # resources per tie	-2.844 (1.918)	-2.546*** (0.477)	-4.381*** (1.256)			
Resource diversity				-4.408** (1.663)	-2.660*** (0.237)	-2.489*** (0.699)
Constant	-14.82 (1092.2)	1.132*** (0.330)	-15.33 (764.4)	-16.33 (2796.5)	1.533*** (0.355)	-16.75 (1894.3)
Observations	3,105	3,105	3,105	3,105	3,105	3,105

All regressions of multinomial logistic regressions, where the dependent variable is a dummy that takes values from 0-3 for firm failure, IPO, acquisition, and survival; the base outcome for the two multinomial logit is firm survival. Columns 1-3 and 4-6 have average number of resources transferred across each tie and resource diversity as their independent variables, respectively. The results in columns 1-3 are one set of multinomial logistic regression, where one of the independent variables is average number of resources transferred across each tie. The results in columns 4-6 are the other set of multinomial logistic regression, where the independent variable is resource diversity.

Notes. Standard errors in parentheses
$^{*}p < .05$
$^{**}p < .01$
$^{***}p < .001$

Table 15. OLS Regression of Start-up Performance

	(1)	(2)	(3)
	Gross Profit (Loss)	Sales/Turnover (Net)	Net Income (Loss)
Employee start-up	-141.8*	-123.0	-37.84*
	(63.87)	(75.49)	(16.71)
Firm age	-21.87*	-21.15*	-5.415*
	(8.887)	(10.51)	(2.263)
#Patents every year	4.608*	7.306*	1.052**
	(1.964)	(3.240)	(0.386)
#Ties	-17.93*	-19.67	-4.187
	(8.689)	(10.23)	(2.439)
Resource diversity	-679.2***	-823.7***	-145.3***
	(169.4)	(198.1)	(43.01)
USA	261.1**	319.8**	53.78*
	(85.99)	(101.0)	(21.54)
Year controls	Y*	Y*	Y*
Constant	114.8	94.72	24.94
	(92.32)	(111.5)	(24.82)
Observations	2,430	2,430	2,430
R2	0.0216	0.0218	0.0178

The above regressions are OLS estimation of firm gross profits, net sales, and net income.

Notes. Standard errors in parentheses
* $p < .05$
** $p < .01$
*** $p < .001$

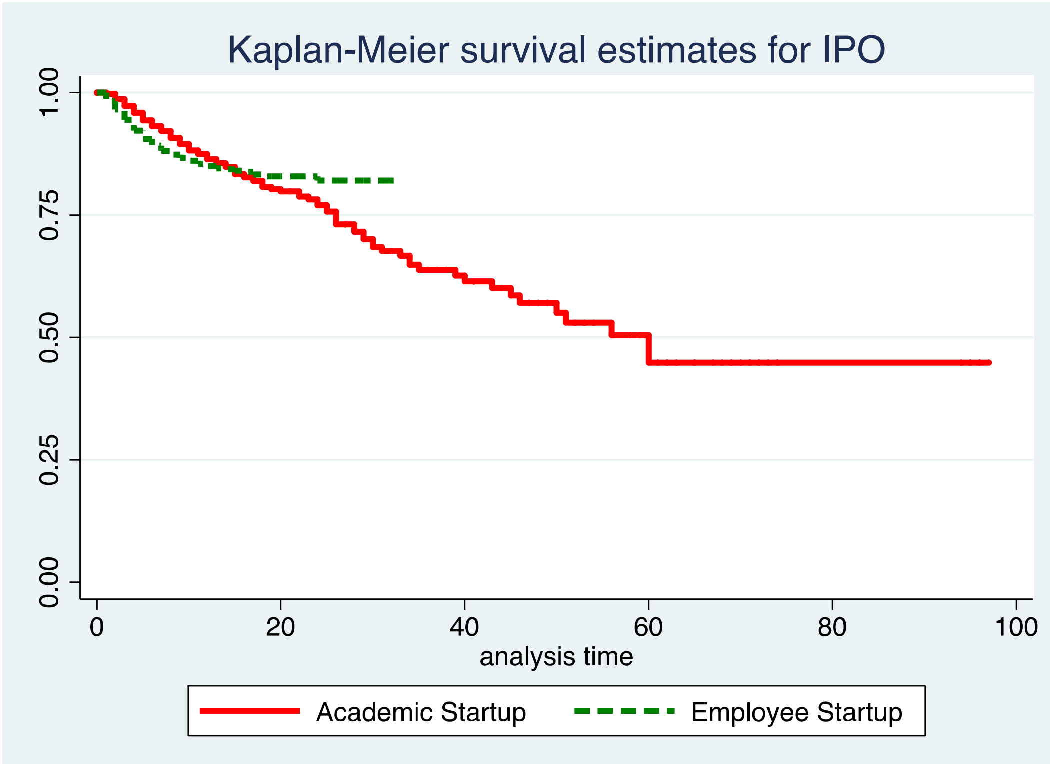
Table 16. Firm Fixed Effects Regression of Start-up Performance

	(1)	(2)	(3)
	Gross Profit (Loss)	Sales/Turnover (Net)	Net Income (Loss)
Employee start-up	-134.7 (491.2)	-166.9 (535.2)	-32.17 (194.9)
Firm age	-0.949 (12.50)	-1.506 (13.62)	-0.00868 (4.959)
#Patents every year	-0.682 (2.301)	-0.782 (2.507)	-0.169 (0.913)
#Ties	63.90 (385.9)	84.49 (420.5)	6.496 (153.1)
Resource diversity	568.9 (2410.7)	651.4 (2626.6)	42.42 (956.3)
USA	60.72 (200.5)	68.99 (218.5)	11.28 (79.54)
Year controls	Y	Y	Y
Constant	-249.5 (2383.2)	-326.9 (2596.7)	-11.53 (945.4)
Observations	2,430	2,430	2,430
R2	0.0475	0.0657	0.0232

The above regressions are firm fixed effects estimations of firm gross profits, net sales, and net income.

Notes. Standard errors in parentheses
$^{*}p < .05$
$^{**}p < .01$
$^{***}p < .001$

Figure 5. Survival Function for Start-ups Going Public



These survival functions show the KM survival estimate curves for employee and academic start-ups for the IPO event of firm.

Table 17. Cox Model Estimating IPO Event

	(1)
	_t
Employee start-up	1.143*** (0.171)
#Employees	-0.0000881 (0.0000972)
USA	1.035 (0.714)
#Patents	0.000269 (0.000237)
#Ties	-0.00438 (0.0174)
Resource diversity	-0.726 (0.407)
Observations	799

This is a Cox model estimating the event of an IPO using Breslow's approximation. The Wilcoxon test for equality of survival curves suggests that the Breslow's approximation is a better specification.

Notes. Standard errors in parentheses
$^{*}p < .05$
$^{**}p < .01$
$^{***}p < .001$

Bibliography

Agarwal, R., Echambadi, R., Franco, A. M., & Sarkar, M. 2004. Knowledge transfer through inheritance: Spin-out generation, development, and survival. ***Academy of Management Journal***, 47(4): 501-522.

Agarwal, R., Ganco, M., & Ziedonis, R. H. 2009. Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. ***Strategic Management Journal***, 30(13): 1349-1374.

Agarwal, R., & Shah, S. K. 2013. ***Knowledge sources of entrepreneurship: Firm formation by academics, users and employees***. Working paper, University of Maryland.

Agarwal, R., & Shah, S. K. 2014. Knowledge sources of entrepreneurship: Firm formation by academic, user, and employee innovators. ***Research Policy***, 43(7): 1109-1133.

Ahuja, G. 1996. Collaboration and innovation: ***A longitudinal study of interfirm linkages and firm patenting performance in the global advanced material industry***. Doctoral dissertation, University of Michigan Business School.

Aiken, M., & Hage, J. 1968. Organizational interdependence and intra-organizational structure. ***American Sociological Review***, 33(6): 912-930.

Audretsch, D. B., & Stephan, P. E. 1996. Company-scientist locational links: The case of biotechnology. ***The American Economic Review***, 86: 641-652.

Baum, J. A. C., Calabrese, T., & Silverman, B. S. 2000. Don't go it alone: Alliance network composition and startups performance in Canadian biotechnology. ***Strategic Management Journal***, 21: 267–294.

Baum, J. A. C., & Oliver, C. 1991. Institutional linkages and organizational mortality. ***Administrative Science Quarterly***, 36: 187–218.

Beckman, C. M., & Burton, M. D., 2008. Founding the future: Path dependence in the evolution of top management teams from founding to IPO. ***Organization Science***, 19(1): 3–24.

Bleeke, J, & Ernst, D., 1993. ***Collaborating to compete: Using strategic alliances and acquisitions in the global market place.*** New York, NY: Wiley.

Bloom, N., Schankerman, M., & Reenen, J. V. 2013. Identifying technology spillovers and product market rivalry. ***Econometrica***, 81(4): 1347-1393 forthcoming.

Boeker, W. 1989. Strategic change: The effects of founding and history. ***Academy of Management Journal***, 32(3): 489-515.

Bonardo, D., Paleari, S., & Vismara, S. 2010. The M&A dynamics of European science-based entrepreneurial firms. ***The Journal of Technology Transfer***, 35: 141-180.

Burgers, W. P., Hill, C. W. L., Kim, W. C. 1993. A theory of global strategic alliances: The case of the global auto industry. ***Strategic Management Journal***, 14(6): 419-432.

Burt, R. S. 1992. Structural holes: ***The Social Structure of Competition***. Cambridge, MA: Harvard University Press.

Chatterji, A. K. 2009. Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. ***Strategic Management Journal***, 30(2): 185-206.

Clarysse, B., Wright, M., & Van de Velde, E. 2011. Entrepreneurial origin, technological knowledge, and the growth of spin-off companies. ***Journal of Management Studies***, 48: 1420-1442.

Cohen, W.M., & Levin, R.C. 1989. Empirical studies of innovation and market structure. ***Handbook of Industrial Organization***, (2): 1059-1107.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive capacity: A new perspective on learning and innovation. ***Administrative Science Quarterly***, 35(1): 128-152.

Davis, J. P., & Eisenhardt, K. M. 2011. Rotating leadership and collaborative innovation: Recombination processes in symbiotic relationships. ***Administrative Science Quarterly,*** 56: 159–201.

Dyer, J. H., & Singh, H. 1998. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. ***Academy of Management Review***, 23: 660-679.

Eisenhardt, K. M., & Schoonhoven, C. B. (1996). Resource-based view of strategic alliance formation: Strategic and social effects in entrepreneurial firms. ***Organization Science***, 7(2): 136–150.

Ensley, M. D., & Hmieleski, K. M., 2005. A comparative study of new venture top management team composition, dynamics, and performance between university-based and independent start-ups. ***Research Policy***, 34: 1091-1105.

Fichman, M., & Levinthal, D. A. 1991. Honeymoons and the liability of adolescence: A new perspective on duration dependence in social and organizational relationships. ***Academy of Management Review***, 16: 442-468.

Franco, A. M., & Filson, D. (2006). Spin-outs: Knowledge diffusion through employee mobility. ***The RAND Journal of Economics***, *37*(4): 841-860.

Ganco, M. 2013. Cutting the Gordian knot: The effect of knowledge complexity on employee mobility and entrepreneurship. ***Strategic Management Journal***, 34(6): 666-686.

Gans, J., & Stern, S. 2003. The product market and the market for ideas. ***Research Policy***, 32(2): 333-350.

Gomes-Casseres, B. 1994. Group versus group: How alliance networks compete. ***Harvard Business Review***, 72(4): 62–74.

Gompers P., Lerner J., & Scharfstein D. 2005. Entrepreneurial spawning: Public corporations and the genesis of new ventures; 1986 to 1999. ***Journal of Finance***, 60(2): 577-614.

Griliches, Z. 1990. Patent statistics as economic indicators: A survey. ***Journal of Economic Literature***, 28: 1661-1707.

Gulati R. 1995a. Does familiarity breed trust? The implications of repeated ties for contractual choices. ***Academy of Management Journal***, 35: 85-112.

Gulati, R. 1995b. Social structure and alliance formation patterns: A longitudinal analysis. ***Administrative Science Quarterly***, 40: 619–652.

Gulati, R. 1999. Network location and learning: The influence of network resources and firm capabilities on alliance formation, ***Strategic Management Journal***, 20(5): 397-420.

Gulati, R., & Gargiulo, M. 1999. Where do interorganizational networks come from? ***American Journal of Sociology***, 104(5): 1439-1493.

Gulati, R., Lavie, D., & Singh, H. 2009. The nature of partnering experience and the gains from alliances, ***Strategic Management Journal***, 30: 1213-1233.

Hallen, B. 2008. The causes and consequences of the initial network positions of new organizations: From whom do entrepreneurs receive investments. ***Administrative Science Quarterly***, 53: 685–718.

Hamel, G., Doz, Y. L., & Prahalad, C. K. 1989. Collaborate with your competitors and win. ***Harvard Business Review***, 67(1): 133-139.

Helfat, C. E., & Lieberman, M. B. 2002. The birth of capabilities: Market entry and the importance of pre-history. ***Industrial and Corporate Change***, 11(4): 725-760.

Hite, J. M., & Hesterly, W. S. 2001. The evolution of firm networks: From emergence to early growth of the firm, ***Strategic Management Journal***, 22: 275–286.

Ingram, P., & Roberts P. W. 2000. Friendships among competitors in the Sydney hotel industry. ***American Journal of Sociology***, 106(2): 387–423.

Jaffe, A. B. 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. ***American Economic Review,*** 76(5): 984-1002.

Katila, R., Rosenberger, J., & Eisenhardt, K. M. 2008. Swimming with sharks: Technology ventures and corporate relationships. ***Administrative Science Quarterly***, 53: 295–332.

Klepper, S. 2002. The capabilities of new firms and the evolution of the US automobile industry. ***Industrial and Corporate Change***, 11: 645-666.

Klepper, S. 2007. Disagreements, spinoffs, and the evolution of Detroit as the capital of the US automobile industry. ***Management Science***, 53: 616-631.

Klepper, S., & Sleeper, S. 2005. Entry by spinoffs. ***Management Science***, 51(8): 1291-1306.

Kogut, B. 1988. Joint Ventures: Theoretical and empirical perspectives. ***Strategic Management Journal***, 9(4): 319–332.

Kogut, B., Shan, W., & Walker, G. 1992. Competitive cooperation in biotechnology: Learning through networks? In N. Nohria & R. Eccles (Eds.) ***Networks and organizations: Structure, form and action.*** Boston, MA: Harvard Business School Press.

Lavie, D. 2007. Alliance portfolios and firm performance: A study of value creation and appropriation in the U.S. software industry. ***Strategic Management Journal***, 28(12): 1187–1212.

Lee K. B., Jr., & Burrill, G. S. 1994. ***Biotech '95: Reform, restructure, renewal***. Palo Alto, CA: Ernst & Young.

Lockett, A., Siegel, D., & Wright, M., & Ensley, M. D. 2005. The creation of spin-off firms at public research institutions: Managerial and policy implications. ***Research Policy***, 34: 981-993.

Lockett, A., & Wright, M. 2005. Resources, capabilities, risk capital, and the creation of university spin-out companies. ***Research Policy***, 34: 1043-1057.

Lowe, R. A. 2002. ***Invention, innovation, and entrepreneurship: The commercialization of university research by inventor-founded firms***. Doctoral dissertation, University of California, Berkeley, CA.

Lowe, R. A., & Ziedonis, A. A. 2006. Overoptimism and the performance of entrepreneurial firms. ***Management Science**, 52*(2): 173-186.

Makadok, R., & Ross, D. G. 2013. Taking industry structuring seriously: A strategic perspective on product differentiation. ***Strategic Management Journal***, 34(5): 509-532.

Mitchell, W., & Singh, K. 1992. Incumbents' use of pre-entry alliances before expansion into new technical subfields of an industry. ***Journal of Economic Behavior and Organization***, 18: 347-372.

Mitton, D. G., 1990. Bring on the clones: A longitudinal study of the proliferation, development, and growth of the biotech industry in San Diego. ***Frontiers of Entrepreneurship Research***: 344-358.

Narin, F., Elliott, N., & Ross, P. 1987. Patents as indicators of corporate technological strength. ***Research Policy***, 16: 143-155.

Nohria, N., and Garcia-Pont, C. 1991. Global strategic linkages and industry structure, ***Strategic Management Journal***, 12: 105-124.

Pfeffer, J., & Salancik, G. R. 1978. ***The external control of organizations: A resource dependence perspective***. New York: Harper and Row.

Phillips, D. J. (2002). A genealogical approach to organizational life chances: The parent-progeny transfer among Silicon Valley law firms; 1946-1996. ***Administrative Science Quarterly***, 47(3): 474-506.

Pisano, G. P. 1990. The R&D boundaries of the firm: An empirical analysis, ***Administrative Science Quarterly***, 35: 153–176.

Podolny, J. M. 1993. A status-based model of market competition. ***American Journal of Sociology***, 98: 829–872.

Podolny, J. M., Stuart, T. E., & Hannan, M. T. 1996. Networks, knowledge, and niches: competition in the worldwide semiconductor industry; 1984-1991. ***American Journal of Sociology***, 102: 659–689.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. ***Administrative Science Quarterly***, 41: 116–145.

Roberts, P. W. & Sterling, A. D. 2012. Network progeny? Pre-founding social ties and the success of new entrants. ***Management Science***, 58(7): 1292-1304.

Rosenkopf, L. & Almeida, P. 2003. Overcoming local search through alliances and mobility. ***Management Science***, 49:751–766.

Rothaermel, F. T. 2001. Complementary assets, strategic alliances, and the incumbent's advantage: An empirical study of industry and firm effects in the biopharmaceutical industry. ***Research Policy***, 30(8): 1235-1251.

Santos, F. M., & Eisenhardt, K. M. 2009. Constructing niches and shaping boundaries: A model of entrepreneurial action in nascent markets. ***Academy of Management Journal***, 52(4): 643- 671.

Schmidt, S. M., & Kochan, T. A. 1977. Interorganizational relationships: Patterns and motivations. ***Administrative Science Quarterly***, 22: 220-234.

Semadeni M., & Cannella A. 2011. Examining the performance effects of post spin-off links to parent firms: Should the apron strings be cut? ***Strategic Management Journal***, 32(10): 1083-1098.

Shane, S. A. 2004. ***Academic entrepreneurship: University spinoffs and wealth creation.*** Cheltenham, UK: Edward Elgar Publishing**.**

Snijders T. A. B., 2002. Markov Chain Monte Carlo estimation of exponential random graph models. ***Journal of Social Structure***, 3(2): 2-40.

Stinchcombe, A. L. 1965. Social structure and organizations. In J. G. March (Ed.), ***Handbook of Organizations***, vol 7: 142-193. Chicago: Rand McNally & Co.

Stuart, T. E., & Ding, W. W. 2006. When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences. ***American Journal of Sociology***, 112: 97-144.

Stuart, T. E., Ozdemir, S. Z., & Ding, W. W. 2007. Vertical alliance networks: The case of university–biotechnology–pharmaceutical alliance chains. ***Research Policy***, 36: 477-498.

Stuart, T. E., & Sorenson, O. 2003a. The geography of opportunity: Spatial heterogeneity in founding rates and the performance of biotechnology firms. ***Research Policy***, 32: 229-253.

Stuart, T. E., & Sorenson, O. 2003b. Liquidity events and the geographic distribution of entrepreneurial activity. ***Administrative Science Quarterly***, 48(2): 175-201.

Vohora, A., Wright, M., & Lockett, A. 2004. Critical junctures in the development of university high-tech spinout companies. ***Research Policy***, 33: 147-175.

Wennberg, K., Wiklund, J., & Wright, M. 2011. The effectiveness of university knowledge spillovers: Performance differences between university spinoffs and corporate spinoffs. ***Research Policy***, 40: 1128-1143.

Williamson, O. E. 1991. Comparative economic organization: The analysis of discrete structural alternatives. ***Administrative Science Quarterly***, 36: 269–296.

Winston Smith, S., & Shah, S. K. 2013. Do innovative users generate more useful insights? An analysis of CVC investment in the medical device industry. ***Strategic Entrepreneurship Journal***, 7:151-167.